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"Leadership in the Age of AI: Integrating Ethical Practices and Decision-Making Styles"

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1. Introduction

Artificial intelligence (AI) has rapidly transformed the technological and industrial landscape. Its ability to analyze massive amounts of data, learn from it and make decisions autonomously has revolutionized not only the way organizations operate, but also the role of leadership in driving such transformations. As AI continues to penetrate every aspect of business operations, from logistics to marketing, there is a growing need to understand how this technology is affecting traditional leadership models and how leaders can adapt to this new context. However, despite the extensive literature on the impact of AI on business operations, its specific effect on leadership has so far been relatively ignored. This study aims to fill that gap by providing a deeper understanding of how AI is redefining leadership models within contemporary organizations.

In particular, the research focuses on two key questions that guide the analysis. The first research question is, *"How does Artificial Intelligence redefine leadership models within contemporary business organizations?"* This question comes from the need to explore how AI is transforming the role of leaders and traditional leadership models. In a context where AI is no longer just an option, but a necessity to remain competitive, leaders must not only be technically competent, but also ethically aware and able to navigate complex organizational and technological dynamics. This study aims to outline the new leadership requirements needed to lead organizations through the AI revolution, highlighting the skills, behaviors, and qualities leaders must develop to succeed in this new context.

The second research question explores the internal variables that influence leaders' attitude toward the adoption of AI: *"Which are the underlying variables shaping leaders' attitude toward the adoption of AI?"* This question is critical to understanding what factors determine leaders' propensity to embrace AI as a strategic tool in their organizations. This thesis investigates how ethical leadership, decision-making styles, and attitudes toward AI interact to influence AI adoption, providing a conceptual map of the dynamics at play.

The existing literature up to now has examined many of the elements covered in this thesis separately, but has rarely explored the interconnections between leadership, decision-making, and AI adoption in an integrative way. This study, therefore, not only addresses a practical need but also a theoretical gap by proposing a conceptual framework that ties these dimensions together to offer a more holistic view of leadership in the AI era.

Through an in-depth theoretical and empirical analysis, this research aims to answer these fundamental questions, contributing to a better understanding of the challenges and opportunities that AI presents for leadership. Moreover, the findings will offer new perspectives for both theory and practice, suggesting development paths for leaders facing the challenges of digital transformation. Overall, this thesis aims to make a significant contribution to the existing literature, enriching the debate on how AI is shaping the future of organizations and leadership.

2. AI and Leadership

Artificial Intelligence is becoming more widespread in today's businesses, completely changing how they function and compete. From process automation to market trend forecasting, from automating processes, to predicting market trends, AI has become a key element for many organizations (Brynjolfsson & McAfee, 2017). This transformation not only affects business operations but also changes how leaders carry out their responsibilities. Integrating AI into decision making processes empowers leaders to make more informed decisions and efficiently manage resources (Ransbotham et al., 2017). Leading in an era dominated by AI demands a deep dive on emerging technologies and their strategic implications.

As the use of AI continues to grow ethical concerns also come to the forefront that must be addressed. Issues like transparency, fairness and accountability pose challenges that leaders must address when implementing AI systems (Floridi et al., 2018). Ethical leadership is therefore essential to ensure that AI usage aligns with the values and norms of the organization fostering sustainable adoption practices. This chapter delves into the basics of AI evolution within the business realm and its diverse applications, across industries. It will examine how AI impacts leadership models and delve into theories of leadership in the age of AI.

2.1. Foundation of AI

Artificial Intelligence includes a wide range of technologies and techniques pointed at creating systems capable of performing tasks that usually require human intelligence. These tasks include reasoning, learning, problem-solving, perception, and language understanding (Russell & Norvig, 2016). AI's scope spans various fields, from simple rule-based systems to complex neural networks and autonomous systems, showcasing its versatile nature and wide-ranging applicability (Schneider et al, 2016).

Historically, the formal establishment of AI as a scientific field occurred in the mid-20th century. Alan Turing's groundbreaking 1950 paper, "Computing Machinery and Intelligence," questioned whether machines could think and introduced the Turing Test. Turing introduced this test to evaluate machine intelligence. In this test, a human evaluator communicates with both a machine and another human through a computer interface. If the evaluator cannot reliably tell which responses come from the machine and which come from the human, the machine is considered to exhibit human-like intelligence (Turing, 2009). Then, the term "Artificial Intelligence" was officially introduced by John McCarthy in 1956 at the Dartmouth Conference, marking the beginning of AI as a formal discipline (McCarthy et al., 2006).

Over the decades, AI has experienced several crucial phases of development. The initial excitement of the 1950s and 1960s, marked by the creation of early AI programs was a period of high optimism. Main AI programs from this era included the Logic Theorist (1956) by Allen Newell and Herbert A. Simon, which could prove mathematical theorems (Gugerty, 2006), and the General Problem Solver (1957), designed to be a universal problem-solving machine (Simon, 1989). Another notable project was ELIZA (1964), an early natural language processing program developed by Joseph Weizenbaum that simulated conversation by matching user inputs to pre-scripted responses (Weizenbaum, 1966). The first industrial robot, Unimate, was introduced during 1961 and began operating at General Motors, marking a significant milestone by replacing human workers on the assembly line (Detesan & Moholea, 2024). Five years later, in 1966, Stanford developed Shakey the robot, which became the first general-purpose mobile robot capable of reasoning about its actions. Shakey's development was a significant milestone in robotics, as it integrated perception, movement, and decision-making capabilities, paving the way for more advanced autonomous systems (Kuipers et al., 2017).

However, this initial optimism was followed by periods of skepticism and reduced funding known as "AI winters." The first AI winter in the early 1970s was caused by limitations in computational power and AI systems' inability to solve complex problems as initially expected (Hendler, 2008). The Lighthill report (1973) in UK criticized the progress in AI research, leading to reduced funding. The second AI winter occurred in the late 1980s and early 1990s due to the collapse of the market for specialized AI hardware, and the failure of many AI projects to meet their ambitious promises (Toosi et al., 2021).

Despite these setbacks, the field of AI experienced a resurgence in the late 20th and early 21st centuries. This revival was driven by significant advancements in machine learning, the availability of large datasets, and increased computational power. During this period, new algorithms and techniques were developed, significantly enhancing the capabilities of AI systems (Pagallo et al., 2018).

During 1997, IBM's Deep Blue gained a lot of attention by defeating the world chess champion Garry Kasparov, demonstrating the significant capabilities of AI in executing complex strategic tasks (Newborn & Newborn, 2003). This moment was a key event in AI history, proving that AI could excel in areas that require advanced problem-solving and strategic thinking. The next year, in 1998, Cynthia Breazeal from MIT presented Kismet, a robot designed to recognize and respond to human emotions (Breazeal, 2004).

At the turn of the millennium, AI started to be increasingly integrated into consumer products. In 1999, Sony introduced AIBO, the first consumer robot pet dog with AI capabilities that could develop its personality over time (Sone, 2016). This was followed by iRobot's release of Roomba in 2002, the first widely available autonomous robotic vacuum cleaner, which revolutionized home cleaning by navigating and cleaning homes independently (Forlizzi & DiSalvo, 2006).

The 2010s saw significant advancements in the integration of AI in everyday technology. In 2011, Apple launched Siri, an intelligent virtual assistant with a voice interface, launched into the iPhone 4S for the first time, thereby making AI accessible to millions of users (Reis et al., 2018). The same year, IBM's Watson demonstrated its advanced question-answering abilities by winning first place on the television quiz show Jeopardy! (Ferrucci et al., 2013). In 2014, a chatbot named Eugene Goostman successfully passed the Turing Test mentioned before by persuading one-third of the judges that it was a human (Neufeld & Finnestad, 2020). Furthermore, Amazon introduced Alexa, a virtual assistant capable of voice interactions for various tasks (Lopatovska et al., 2019).

However, not all developments had a positive impact on the society. In 2016, Microsoft's chatbot Tay was taken offline after it posted offensive comments on social media (Neff, 2016). Although this incident, AI continued to achieve remarkable success, like in 2017 when Google's AlphaGo defeated world champion Ke Jie in the board game Go, which is known for its vast number of possible positions (Brunner, 2019).

Keeping in mind the history of AI, it is evident that the journey has been one marked by remarkable achievements and significant challenges. The early aspirations, followed by subsequent disappointments, underscore the deep complexity in replicating human intelligence. However, the continuous advancements in technology and methodologies highlight the potential of AI. Today, AI has permeated various aspects of life and industry, showcasing its transformative power. The lessons learned from past experiences show the importance of maintaining a balanced perspective, fostering innovation while addressing ethical and society concerns, ensuring that it continues to advance in ways that benefit humanity.

In the AI context, ethical and social concerns are crucial. AI systems, if not well designed, can reinforce biases present in the training data, leading to unfair or discriminatory outcomes. For example, biased algorithms in hiring processes or law enforcement can perpetuate societal inequalities, highlighting the crucial need for developing methods to detect and mitigate bias in AI models (Tippins et al., 2021). Ensuring transparency and accountability in AI decision-making processes is essential to gain public trust and acceptance (Mittelstadt et al., 2016).

Looking at the future, Artificial Intelligence offers enormous promise and potential. Emerging trends, such as ethical and responsible AI, aim to ensure that decisions made by AI are safe and respect the rights of individuals, which is essential for critical applications in areas such as healthcare, finance, and other fields where trust is paramount. In support of these principles, the AI Act, which will be in effect in Europe from next year, establishes a regulatory framework to ensure the safe and transparent use of AI (Helberger & Diakopoulos, 2023).

2.2. Implementation AI in Business

Artificial Intelligence has become an indispensable part of the business landscape, driving innovation, enhancing operational efficiency, and enabling strategic decision-making. The effectiveness of AI in the business context cannot be overstated, as it allows companies to process vast amounts of data, uncover insights, and automate processes that were previously handled manually (Russell & Norvig, 2016). AI technologies lead to more informed decision-making thanks to predictive analytics on real-time data, which are crucial in today's fast-paced market environments. For instance, AI-powered tools can analyze market trends, customer behavior, and operational performance, offering businesses a competitive edge through improved forecasting and strategic planning (Gartner, 2018).

According to McKinsey (2024), the percentage of enterprises employing AI technologies grew from 20% in 2017 to 72% in 2024, reflecting a significant increase in AI integration across various sectors (McKinsey & Company, 2024). AI has been instrumental in improving process efficiencies, such as predictive maintenance in manufacturing and dynamic pricing in retail. For example, in the manufacturing sector, AI-driven predictive maintenance has reduced equipment downtime by up to 30%, leading to substantial cost savings and increased productivity (McKinsey & Company, 2024).

The growing reliance on AI is also reflected in the significant investments made by companies. According to Goldman Sachs (2023) global investments in AI could arrive to around $200 billion globally by 2025, highlighting the recognition of AI's potential (Goldman Sachs, 2023).

AI has a profound impact also on productivity and efficiency. AI-driven automation has increased the speed of processes, reduced errors, and improved overall quality. For example, according to McKinsey (2024) AI could be able to deliver additional global economic activity of around $13 trillion by 2030, or about 16% higher cumulative GDP compared with today. Specific metrics, such as a 30% reduction in operational costs and a 40% increase in production speed, highlight the transformative potential of AI (McKinsey & Company, 2024).

In addition to enhancing operational efficiencies, AI technologies are central to the digital transformation strategies of many organizations, driving significant changes in how businesses operate and compete. AI impact on strategic planning and decision-making is substantial, with 94% of executives reporting that AI will be a business advantage in the future (Deloitte, 2022). The integration of AI in digital platforms enhances customer experiences and operational efficiencies across various sectors (Harvard Business Review, 2020).

AI impact extends beyond the micro-level improvements in individual processes and touches also the macro-level, fundamentally altering organizational structures. AI-driven organizational models have emerged to accommodate and leverage these technologies, creating frameworks that emphasize agility, flexibility, and data-driven decision-making, which are crucial for being competitive in today’s dynamic business environment.

AI profoundly shape organizational structures, often resulting in flatter hierarchies and more agile frameworks. Traditional, rigid hierarchies are being replaced by dynamic and responsive organizational forms. For instance, many companies are now adopting the Agile structure. Agile organizations emphasize flexibility, speed, and a customer-centric approach. They are designed to swiftly adapt to evolving market conditions and customer needs. In the Agile structure, teams are typically small and cross-functional, working in iterative cycles to deliver incremental value (Denning, 2016). This approach is especially effective in AI environments, where rapid experimentation and continuous improvement are crucial (Rigby et al, 2016). By embracing the Agile Structure, organizations can improve their responsiveness and innovation, staying ahead in the competitive environment.

The Lean structure is the last organizational structure increasingly adopted by AI-driven organizations. Lean organizations prioritize maximizing value while minimizing waste, emphasizing efficiency, continuous improvement, and the elimination of non-value-adding activities (Womack & Jones, 2003). AI represent a crucial element in the lean structures by automating repetitive tasks, identifying inefficiencies, and providing data-driven insights for decision-making. The integration of AI in Lean organizations helps streamline processes and enhance overall productivity (Sharma & Pinca-Bretotean, 2023).

Shifting from organizational structures to roles and responsibilities, we observe that new employee positions are emerging as organizations adapt to AI. Roles such as Chief AI Officer, data scientists, and AI ethicists are becoming increasingly common and are essential for managing AI initiatives, ensuring ethical AI use, and integrating AI capabilities inside the organization.

The Chief AI Officer oversees the AI strategy, ensuring that AI initiatives align with business objectives and regulatory requirements. This role involves building AI capabilities within the organization, managing AI projects, and fostering a culture that enhance AI. Data scientists, instead, are tasked with developing models, analyzing data, and providing actionable insights to support decision-making. Their operational expertise is crucial for turning data into strategic assets (Lamarre et al., 2024). AI ethicists focus on the ethical use of AI, ensuring transparency, fairness, and accountability in AI applications (Davenport, 2019). They have a crucial role in addressing the moral and ethical implications of AI, ensuring that AI systems operate in a manner that is fair and equitable. A critical aspect of their role is to identify and mitigate biases within AI systems. AI ethicists work to develop guidelines and practices that promote unbiased data collection, algorithmic transparency, and equitable decision-making processes.

Despite the transformative potential of AI, many organizations struggle with significant cultural and organizational obstacles to its widespread adoption. One major barrier is the embedded traditional mindset and established ways of working, which often conflict with the demands of AI. For instance, numerous companies still operate in silos, where departments function independently rather than collaboratively (Kar et al., 2021).

To overcome these problems, organizations need to make several strategic shifts. Firstly, they must move from siloed work environments to fostering interdisciplinary collaboration. AI initiatives are more useful when developed by cross-functional teams that combine diverse skills and perspectives (Fountaine, McCarthy, & Saleh, 2019). Secondly, decision-making processes need to shift from being experience-based and leader-driven to data-driven and decentralized. Empowering employees at all levels to make decisions based on AI insights can significantly improve the quality and speed of decision-making. Lastly, organizations must embrace agility, experimentation, and adaptability. Adopting a test-and-learn mentality could help to reframe mistakes as learning opportunities, reducing the fear of failure and accelerating the development and deployment of AI solutions (Fountaine, McCarthy, & Saleh, 2019). By making these strategic shifts, companies can better integrate AI into their operations, driving innovation and enhancing overall performance.

In conclusion, while AI continues to revolutionize business operations by reshaping efficiencies, productivity, and strategic planning at a micro level, its impact on the macro level—specifically on organizational models—highlights the need for a comprehensive approach to AI integration. The next subparagraph will explore significant improvement at the micro level across various industries, showcasing AI's widespread and transformative effects.

2.2.1. AI Application across Industries

Following the discussion on trends and benefits brought by AI, this subparagraph will delve into the industries most significantly impacted by this technology. The applications of AI are various, influencing numerous sectors and revolutionizing traditional practices in unprecedented ways.

Starting from the healthcare industry, AI is revolutionizing diagnostics, treatment planning, and patient care. AI-driven systems can analyze medical images often surpassing human capabilities. For instance, deep learning algorithms are used to detect anomalies in radiology images, enabling earlier and more accurate diagnoses of conditions such as cancer and heart disease (Albawi et al., 2023). Companies like Zebra Medical Vision and Aidoc are at the front line in this field, providing advanced AI solutions for medical imaging (Milam & Koo, 2023). Additionally, AI-powered tools assist in personalized medicine by analyzing patient data to recommend tailored treatment plans. IBM Watson Health is a notable example, leveraging AI to help healthcare providers make more informed clinical decisions (IBM Watson Health, 2023).

We can also find use cases in the financial sector, which is another area where AI has made significant improvements. AI algorithms are largely used for risk management, fraud detection, and algorithmic trading. Machine learning models analyze transaction patterns to identify fraudulent activities in real-time, allowing banks to have robust security measures (Ngai et al., 2021). For instance, JPMorgan Chase uses AI to detect fraud and manage risks more effectively. Furthermore, AI-driven predictive analytics enable financial institutions to make informed decisions about investments and credit risk

(El Hajj & Hammoud, 2023). BlackRock, a global investment management corporation, indeed, employs AI to analyze market data and guide investment strategies (Barua & Barua, 2024). Additionally, AI-powered robo-advisors, such as Betterment and Wealthfront, offer personalized financial advice, democratizing access to investment management (Kishore et al., 2024).

Transportation and logistics have also been significantly transformed by AI, particularly through the development of autonomous vehicles and the optimization of logistics operations. AI technologies allow self-driving cars and trucks to drive autonomously, ideally reducing accidents and improving traffic flow (Siegel & Pappas, 2023). Tesla's Model S and Model 3, for example, use AI for their Autopilot system, demonstrating advanced self-driving capabilities. In logistics, AI leads to optimal outcomes in route planning and fleet management, enhancing delivery efficiency and reducing fuel consumption (Tsolaki et al., 2023). Companies like UPS and DHL leverage AI to optimize their delivery routes and improve logistics efficiency. Furthermore, AI-powered drones are being explored for delivery, offering innovative solutions to traditional logistics challenges. Amazon Prime Air, for instance, is launching drone delivery to revolutionize the logistics industry (Schwieterman & Craig, 2023).

Turning to retail and e-commerce, AI has profoundly impacted these sectors mainly through personalization and supply chain optimization. AI algorithms analyze customer data to deliver personalized shopping experiences, recommending products based on individual preferences and behaviors (Ajiga et al., 2024). Amazon and Alibaba are pioneers in this field. On the supply chain front, AI optimizes inventory management by predicting demand and adjusting stock levels, accordingly, reducing waste and improving operational efficiency (Choi et al., 2018). According to this, Walmart makes use of AI to streamline its supply chain operations, ensuring products are available when and where customers need them. Additionally, AI-powered chatbots and virtual assistants enhance customer service by handling inquiries and providing support at any time. For instance, companies like H&M and Sephora are employing these technologies to improve customer experience (Kumar et al., 2024).

In the manufacturing sector, instead, AI drives advanced automation and enhances predictive maintenance. AI-powered robots and automation systems significantly boost production efficiency and effectiveness, thereby reducing human error and operational costs (Kim et al., 2022). In particular, predictive maintenance algorithms analyze machinery data to forecast potential failures before they happen, which minimizes downtime and extends the lifecycle of equipment (Zonta et al., 2020). For instance, Airbus employs AI for predictive maintenance, ensuring the reliability and safety of its aircraft. Moreover, AI is now essential in quality control, utilizing computer vision to inspect products for defects (Wang et al., 2019).

In the energy sector, the last industry we will explore, AI is being leveraged to enhance efficiency and sustainability. By analyzing data, AI algorithms can optimize energy production and distribution, balancing supply and demand in real-time (Rinku, 2023). Prominent companies like General Electric are at the forefront of using this technology to improve energy systems. In the field of renewable energy, AI plays a critical role in predicting weather to maximize the performance of solar panels and wind turbines, thereby improving the reliability and efficiency of green energy sources (Ohalete et al., 2023). Moreover, AI contributes to energy conservation through intelligent energy management systems for buildings, which help reduce consumption and costs. Companies like Johnson Controls and Honeywell are leading the way in implementing AI-driven energy management solutions (Dounis, 2010). This integration of AI not only enhances operational efficiency but also supports the transition towards more sustainable energy practices, making a significant impact on both the industry and the environment.

The comprehensive exploration of AI applications across various industries highlights the transformative power of artificial intelligence. Each sector, from healthcare to energy, has demonstrated significant improvements through AI integration. As AI technology continues to evolve, its applications are expected to expand further, fostering innovation, and driving competitiveness in the global market.

2.3. Theories of Leadership

Having explored the transformative impact of AI across various industries, it is now essential to discuss how AI intersects with leadership. Leadership is nothing more than the ability to guide, influence and motivate a group of followers or an organization toward the achievement of common goals. It has always been an essential element of organizational success, crucial for inspiring teams, driving innovation, and achieving strategic goals. As the business environment evolves with the integration of Artificial Intelligence, it becomes crucially important to examine how traditional leadership theories adapt and transform in this new context. This paragraph provides an overview of established leadership theories. By understanding these theories, we can better appreciate the evolving role of leaders in an AI-driven world and how they can leverage this technology to enhance their leadership effectiveness.

One of the earliest approaches to leadership is the *Trait Theory*, which suggests that individuals are born with qualities that make them, or not, effective leaders. These traits include attributes such as intelligence, self-confidence, determination, integrity, and sociability (Northouse, 2021). Over time, Trait Theory has evolved to incorporate the Big Five Personality Traits, also known as the CANOE framework: Conscientiousness, Agreeableness, Neuroticism, Openness to Experience, and Extraversion. Research has demonstrated that these traits are significant predictors of leadership emergence. For example, extraversion is strongly associated with leadership emergence and effectiveness, while conscientiousness and openness to experience are linked to positive leadership outcomes (Shahzad et al., 2021). However, despite its contributions, Trait Theory has faced criticism for its deterministic nature and its failure to account for situational factors (Clark & Harrison, 2018). This critique highlights the need for a more nuanced understanding of leadership that considers both individual traits and the contexts in which leadership is exercised.

Shifting the focus from inherent traits to observable behaviors, the *Behavioral Theory* of leadership (Lewin et al, 1950) states that effective leadership depends on specific behaviors that can be learned and developed. This theory categorizes leadership styles into three main types: autocratic, democratic, and laissez-faire (Yukl, 1971). Autocratic leaders make decisions unilaterally, democratic leaders involve team members in the decision-making process, and laissez-faire leaders provide minimal direction, allowing team members to make decisions independently. The effectiveness of these styles can vary depending on the context, underscoring a limitation of the Behavioral Theory, which shows the need for a more flexible approach to leadership that considers situational factors and the dynamics of each group of followers (Mosley, 1998).

The *Contingency Theory* of leadership, instead, argue that a leader's ability depends on how well their leadership style aligns with the context or situation at hand (Fiedler et al, 1960). One of the most prominent models within this theory is Fiedler's Contingency Model, which evaluates leaders based on their orientation—whether they are task-oriented or relationship-oriented—and the favorableness of the situation (Fiedler, 2006). Another important model is the *Path-Goal Theory*, which argues that leaders should adapt their style to meet the needs of their followers and the work environment to achieve desired outcomes (House, 1971). This theory highlights the importance of situational variables in shaping the most effective leadership style. For instance, in a stressful environment, a leader might adopt a supportive approach to increase morale, whereas a directive style could be more effective in a highly structured, routine task environment.

Transformational and Transactional leadership theories, developed by Burns (1978) and Bass (1985), offer opposite perspectives on how leaders motivate and influence their followers. Transformational leadership is marked by the ability to inspire and motivate followers to achieve extraordinary outcomes and to engage in continuous improvement (Bass, 1990). Transformational leaders are often seen as visionaries who can drive significant change through their charisma, inspirational motivation, intellectual stimulation, and individualized consideration (Avolio & Yammarino, 2013).

In contrast, Transactional leadership focuses on the exchanges that occur between leaders and followers, where leaders provide rewards or punishments based on the performance of the follower (Tavanti, 2008). This approach emphasizes routine activities, supervision, and performance. Different studies have shown that transformational leadership is more effective in driving innovation and achieving long-term success, whereas transactional leadership is effective in maintaining stability and achieving short-term goals (Brymer & Gray, 2006). This distinction highlights the different ways leaders can impact their organizations. Understanding these theories provides valuable insights into how leadership styles can be personalized to meet various organizational needs and challenges.

Turning to contemporary approaches to leadership, *Servant Leadership* emphasizes the leader's role as supporter of their team. Proposed by Robert K. Greenleaf (1970), this model focuses on the growth and well-being of individuals and the communities they belong to. Servant leaders prioritize the needs of their followers, encouraging personal development and fostering a collaborative work environment leading to higher employee satisfaction, increased trust, and stronger organizational performance (Liden et al., 2008).

Strategic Leadership represents another style that has recently gained prominence. This approach focuses on a leader's ability to anticipate, envision, maintain flexibility, and empower others to drive strategic change (Boal & Hooijberg, 2000). Strategic leaders excel at navigating the uncertainties of the global market, aligning resources with strategic goals, and promoting a culture of continuous improvement and innovation. Contemporary leaders balance short-term operational efficiency with long-term strategic objectives, ensuring the organization's sustainability and competitive advantage. This dual focus allows strategic leaders to adapt to rapid changes and stay ahead in a competitive landscape (Kouzes & Posner, 2023).

2.4. Impact of AI on Leadership

Having discussed traditional Leadership theories, it is now possible to analyze how AI shapes them. The integration of AI into organizational processes largely improves leadership capabilities. AI provides leaders advanced tools for data analysis, predictive analytics, and decision-making support. Leaders using AI can make more informed and faster decisions, resulting in improved organizational performance. IBM's Watson Analytics, for instance, assists leaders in making sense of complex data sets, offering predictive insights to shape business strategies. Similarly, Google leverages AI to enhance decision-making processes by analyzing diverse data sources, optimizing operations, and driving continuous innovation (Torre et al., 2019). This use of AI not only streamlines decision-making but also enables leaders to anticipate market changes and maintain competitiveness in a rapidly evolving business environment.

The rise of AI calls for significant changes in the traits and behaviors that define effective leadership, deeply impacting traditional leadership models. Within the framework of *Trait Theory*, AI tools could enhance and complement the inherent qualities of leaders. For instance, leaders with strong analytical skills can leverage AI to enhance their decision-making capabilities, making them even more effective. The ability to process and interpret complex data sets can amplify traits such as conscientiousness and openness, resulting in more efficient and informed leadership.

When it comes to *Behavioral Theory*, AI is transforming the landscape of leadership behaviors. In this case, leaders with a democratic style could use AI to efficiently gather and analyze input from team members, facilitating more inclusive and data-driven decision-making processes. Autocratic leaders might use AI to make rapid, data-driven decisions in high-pressure situations, while laissez-faire leaders may provide team members with AI-driven information and tools, allowing them to work independently and effectively.

The *Contingency Theory*, which emphasizes the alignment between leadership style and situational variables, is particularly enhanced by AI in these years. AI provides leaders actual data and predictive analytics. It’s easy to deduce then that this allows leaders to adapt their styles more precisely to the needs of the moment. For example, in a high-stress, high-stakes environment, AI could help leaders quickly assess the situation and determine whether a more directive or supportive approach is needed.

Transformational leadership, known for inspiring and motivating followers, also could be significantly augmented by AI. Transformational leaders can utilize AI to gather and analyze data that can be used to tailor their motivational strategies, ensuring they effectively address the needs and aspirations of their followers.

Finally, *Transactional leadership* that, as we said before, focuses on rewards and punishments based on performance, could also benefit from AI. For example, AI systems can monitor performance metrics in real-time, providing immediate feedback and enabling leaders to reward or correct behaviors promptly. This can obviously lead to more efficient and effective management of performance and behavior,

To conclude, the intersection of AI into the business environment has a profound impact on leadership theories. Although the core principles of Trait, Behavioral, Contingency, Transformational, and Transactional leadership remain significant, they must evolve to meet the new capabilities and challenges brought about by AI. Leaders in this AI-driven era need to develop new skill sets, adopt data-driven decision-making approaches, and address the ethical complexities that come with AI integration. In the following paragraph, we will explore AI-driven leadership models that can be found in the literature. These models will offer deeper insights into how AI is transforming leadership dynamics in modern business landscape.

2.4.1. AI-Driven Leadership Models

As stated before, the incorporation of AI technologies into leadership practices becomes more and more essential. Leaders must evolve with these changes to guide their organizations effectively through the dynamic environment that characterize the AI era.

According to Davenport and Foutty, in their article "AI-Driven Leadership" published in MIT Sloan Management Review (2020), AI-oriented leaders must exhibit seven key attributes in order to be able to effectively integrate artificial intelligence into their leadership practices:

1. **Mastering AI Technologies:** AI-driven leaders recognize the importance of understanding AI capabilities and applications. This awareness allows them to make informed decisions and effectively spearhead AI initiatives.
2. **Defining Clear Business Objectives:** Just as with any other technology, it is crucial to have well-defined goals for AI usage. AI-driven leaders ensure that AI initiatives are aligned with the organization's strategic goals, providing clear direction and purpose.

3. **Balancing Ambition with Realism:** Setting the right level of ambition is essential for success. AI-driven leaders establish achievable targets to prevent setbacks from overly ambitious goals, ensuring steady and sustainable progress in AI adoption.
4. **Planning Beyond Initial Phases:** Effective AI leaders look beyond pilots and proofs of concept, planning for full-scale implementation. They evaluate the potential of AI projects to ensure long-term viability and scalability.
5. **Preparing the Workforce:** AI-driven leaders focus on fostering collaboration between humans and AI. This involves preparing employees to work alongside AI, learning new skills, and adopting new roles to maximize the benefits of AI integration.
6. **Prioritizing Data Management:** Recognizing data as a critical asset, AI-driven leaders ensure they have access to the necessary data for meaningful AI work. Effective data management forms the backbone of successful AI initiatives.
7. **Facilitating Interdisciplinary Collaboration:** Promoting teamwork across various departments is essential for integrating AI effectively. AI-driven leaders foster a culture of interdisciplinary collaboration, ensuring that AI is seamlessly incorporated into organizational practices. This approach, sometimes referred to as “symphonic leadership,” involves leaders working together like an orchestra, ensuring that all parts of the organization move harmoniously towards the common goal of AI integration (Davenport & Foutty, 2020).

The concept of AI-driven leadership is gaining relevance as organizations realize the importance of incorporating AI into their leadership models. AI-driven leadership encompasses all key attributes of the AI driven Leader just discussed. This leadership approach basically involves the application of AI to enhance decision-making and improve operational efficiencies.

AI-driven leadership is a strategic and operational approach that leverages AI tools to enhance the capabilities of leaders. By utilizing AI for predictive decision-making and complementing human judgment with AI insights, leaders can make more informed and timely decisions. Additionally, AI-driven leadership involves addressing cultural and ethical considerations, ensuring that the use of AI aligns with organizational values and promotes transparency, inclusivity, and accountability (Titareva, 2021).

However, going into detail, according to Canals and Heukamp in their book “The future of management in an AI world: redefining purpose and strategy in the fourth industrial revolution” (2020), AI can be utilized by innovative leaders in several practical ways:

- **Utilizing AI for Predictive Decision-Making:** AI technologies enable leaders to analyze large amounts of data to forecast outcomes and identify potential challenges before they become apparent. This capability could support strategic planning and risk management.
- **Enhancing Human Decision-Making:** Effective leadership requires a blend of AI-generated insights and human judgment. Leaders integrate the information provided by AI tools with their own experience and intuition to guide their organizations wisely.
- **Addressing Cultural and Ethical Considerations:** AI-driven leaders must navigate the ethical implications of AI technology within their organizations. This includes managing issues such as data privacy, bias in AI algorithms, and the impact of AI on employment. Leaders must foster a culture that values transparency, inclusivity, and accountability.

As we have just seen, addressing cultural and ethical considerations is particularly relevant, as it aligns with the broader scope of Ethical Leadership. The concept of Ethical Leadership in the age of AI, will be the focus of the next paragraph, where we delve deeper into the principles and practices of Ethical Leadership and how it intersects with the adoption of AI.

2.5. Ethical Leadership and AI adoption

Nowadays, the theme of ethics in the world of organizations has assumed fundamental importance. Over the past decades, there has been a growing recognition of the need to integrate ethical considerations into business practices, driven initially by movements advocating for social and environmental sustainability. These movements highlighted the importance of aligning organizational strategies with broader societal values, fostering a business environment that is not only profitable but also socially responsible. As these ethical imperatives gained momentum, they naturally extended to the realm of technological advancements. In particular, the rapid development of AI technologies has amplified the need for ethical leadership. In the era of AI, ethical leadership has become more crucial than ever, as organizations are not only adopting AI to enhance efficiency and innovation but also to ensure that these technologies are integrated in a way that aligns with organizational values and societal norms. The potential ethical challenges associated with AI underscore the necessity for leaders who can navigate these complexities responsibly (Uddin, 2023).

Ethical leadership involves guiding an organization with integrity, transparency, and accountability Such leadership is adopted by leaders who uphold ethical principles and set a positive example for their teams. These leaders make decisions that are not only in compliance with legal standards but are also morally sound, fostering a culture of trust and respect within the organization. Ethical leaders are dedicated to fairness, ensuring their actions and decisions do not harm others and contribute positively to society (Den Hartog, 2015). By prioritizing ethical considerations, these leaders cultivate an environment where ethical behavior is encouraged and valued, promoting a sense of responsibility and community among employees. This commitment to ethical leadership not only enhances organizational integrity but also strengthens its reputation and societal impact.

The 4V Model (see Figure 1), developed by Dr. Bill Grace, offers a comprehensive framework for understanding and practicing ethical leadership. This model includes four essential components: Values, Vision, Voice, and Virtue (Balkac, 2016).

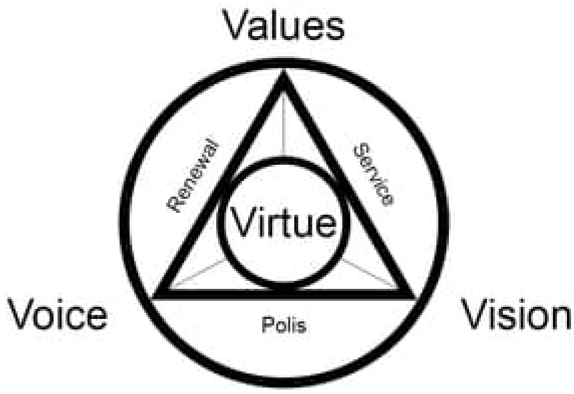

Figure 1: Graphic representation of the 4V Model by Mr. Grace (Mohiuddin et al., 2016)

- **Values:** Ethical leaders base their actions and decisions on a core set of values that reflect principles such as integrity, respect, and fairness. These values guide leaders in making ethical choices and setting a moral tone for the organization.
- **Vision:** Ethical leaders possess a clear vision of what they want to achieve and the means to achieve it. This vision goes beyond organizational success to include the greater good of society and the environment.
- **Voice:** Ethical leaders use their voice to advocate for ethical practices and inspire others to follow their example. They communicate their vision and values clearly and consistently, fostering a culture of transparency and accountability.
- **Virtue:** Ethical leaders embody the virtues they promote. They demonstrate ethical behavior in their actions and decisions, serving as role models for their teams and the broader organization.

By integrating the 4V Model into their leadership practices, leaders can establish a strong ethical foundation that supports responsible AI adoption (Freeman & Auster, 2011). This approach not only enhances organizational integrity but also ensures that AI technologies are implemented in a way that aligns with ethical principles and societal values.

Turning again to AI, the theme of ethics is central in the adoption of artificial intelligence. Ethical leaders ensure that AI systems are designed and implemented in alignment with ethical standards. This involves addressing employee skepticism and potential biases in AI algorithms, ensuring transparency in AI decision-making processes, and protecting data privacy. By fostering a culture of ethical AI use, leaders can enhance trust and acceptance of AI technologies within their organizations (Mohav, 2023).

Ethical leaders also tackle the social implications of AI, such as job displacement. They prioritize strategies for reskilling and upskilling employees, preparing them for new roles in an AI-driven workplace. This approach not only mitigates the negative impacts of AI adoption but also fosters a more adaptable and resilient workforce (Lamarre et al., 2024).

Considering these factors and what the literature suggests, our first research hypothesis states:

H1: "Ethical leadership positively impacts upon AI adoption".

If confirmed, this hypothesis indicates that by integrating ethical principles into AI initiatives, leaders can facilitate smoother and more effective adoption of AI technologies within their organizations.

3. Variables Impacting upon AI adoption

The adoption of Artificial Intelligence within organizations is influenced by a wide range of factors encompassing technological, organizational, and human dimensions. Understanding these variables is crucial for leaders and decision-makers who aim to integrate AI effectively into their business operations (Kurup & Gupta, 2022). This chapter explores the key variables impacting AI adoption, focusing into decision-making theories and the influence of leader' attitudes towards AI. By examining these elements, we aim to provide a comprehensive framework that highlights the complexities and interdependencies involved in adopting AI technologies within modern business environments.

3.1. Theories of Decision Making

Decision-making is a fundamental process within organizations, that shapes strategies, operations, and overall effectiveness. The integration of Artificial Intelligence into business practices introduces a new layer to decision-making, necessitating a deeper understanding of how various decision-making styles influence AI adoption. Decision-making theories offer a framework for understanding how individuals and organizations make choices, evaluate alternatives, and implement decisions (Edwards, 1954).

Decision-making theories can be broadly categorized into normative, descriptive, and prescriptive models (Bell et al.,1988). Normative theories, such as expected utility theory and game theory, want to identify optimal decisions based on rational criteria. The goal of Descriptive theories, like prospect theory, is to explore how decisions are made, often highlighting deviations from rationality due to cognitive biases (Kahneman & Tversky, 1979). Prescriptive theories try to improve decision-making processes by providing tools and frameworks that guide better choices (Bell, 1983).

Keeping the focus on AI adoption, understanding these theories is crucial, as they offer insights into how decision-makers evaluate and implement AI solutions. According to Duan et al. (2019), Normative models assist in identifying the most efficient uses of AI, while descriptive models uncover potential pitfalls and biases that might affect AI adoption. Prescriptive approaches, instead, ensure a more effective integration of AI technologies.

In addition to the theory, also decision-making styles play a central role in how organizations adopt AI, influencing the speed, effectiveness, and overall success of AI implementation. Moreover, decision-making styles could also affect how risks and uncertainties associated with AI are perceived and managed.

To understand the impact of decision-making on AI adoption, it is essential to examine the five primary decision-making styles identified by Scott and Bruce (1995):

- **Intuitive Decision Making**: Relies on instincts and gut feelings.
- **Avoidant Decision Making**: Characterized by procrastination and a reluctance to make decisions.
- **Spontaneous Decision Making**: Involves making quick, impulsive decisions.
- **Rational Decision Making**: Based on logical evaluation and thorough analysis.
- **Dependent Decision Making**: Involves seeking advice and relying on others' input. a dependent decision-making style, which involves seeking advice and consensus from others, can ensure a more comprehensive evaluation but may slow down the decision-making process

In the following subsections a deep dive will be made on each of these styles and how they may interrelate with the adoption of the AI.

3.1.1. Intuitive Decision Making

Intuitive decision making relies on instincts, gut feelings, and immediate judgments. This approach is frequently employed in situations requiring quick decisions under uncertainty. This style of decision making occurs very fast and depends on individual's experiences and perceptions rather than structured and rational analysis. It is commonly used in dynamic and uncertain environments where time constraints and the need for quick responses are critical (Scott & Bruce, 1995).

Intuitive decision making could significantly impact with the adoption of AI technologies. Leaders who rely on intuition may be more open to experimenting with innovative AI solutions, trusting their instincts to identify potential opportunities. This can lead to the early adoption of cutting-edge AI technologies, promoting a culture of innovation within the organization (Duan et al., 2019).

Intuition plays an important role, especially in the early stages of AI adoption as it can drive innovation and the exploration of new AI applications that may not be immediately evident through rational analysis. However, we must keep in consideration that these intuitive decisions must be integrated with rational evaluations to ensure they are based on a solid understanding of AI capabilities and business needs (Duan et al., 2019).

Based on what has been found in literature, it comes naturally to formulate the first hypothesis inherent in the relationship between decision making and AI adoption *H2a:*

> *"The positive relationship between ethical leadership and AI adoption is positively mediated by intuitive decision-making style"*.

According to this hypothesis, intuitive decision making when aligned with ethical leadership, can enhance the effectiveness of AI adoption by promoting innovative thinking and swift decision-making processes.

3.1.2. Avoidant Decision Making

Avoidant decision making involves procrastination and a reluctance to make decisions. This style is often associated with high levels of stress and anxiety, which can hinder effective decision-making processes. This style is characterized by delaying decisions and avoiding taking responsibility. This is typically observed in individuals who experience high levels of uncertainty and fear of failure (Scott & Bruce, 1995; Loo, 2000). Avoidant decision makers often struggle with decisional conflict and may defer decisions in the hope that problems will resolve themselves or that more information will become available.

In today's business scenario, avoidant decision making could lead to significant delays and missed opportunities. Leaders that adopt this style may hesitate to adopt AI technologies due to perceived risks and uncertainties. This reluctance can prevent organizations from leveraging AI's full potential, resulting in a competitive disadvantage (Duan et al., 2019).

Thanks to the integration of AI into decision-making processes, organizations could provide to avoidant decision makers tools that enhance clarity and reduce uncertainty. For example, AI-driven analytics can present clear, data-backed options that simplify complex decisions, making it easier for avoidant decision makers to commit to a course of action (Davenport & Ronanki, 2018).

Based on what was pointed out in the literature, on the link between Avoidant decision making and AI adoption, we came out with the following hypothesis H2b:

> *"The positive relationship between ethical leadership and AI adoption is negatively mediated by avoidant decision-making style"*.

According to this hypothesis, avoidant decision making can undermine the positive effects of ethical leadership on AI adoption, leading to delays and reduced effectiveness.

3.1.3. Spontaneous Decision Making

Spontaneous decision making is characterized by quick, impulsive decisions made without extensive deliberation. This style can be effective in dynamic environments but can also lead to risks when applied to complex decision-making scenarios (Scott & Bruce, 1995).

Spontaneous decision making is characterized by rapid decisions in response to immediate needs or pressures. It is often driven by an individual's instincts and the urgency of the situation (Loo, 2000). Spontaneous decision makers tend to act quickly, sometimes without fully considering all available information.

Spontaneous decision making could lead to AI adoption, enabling organizations to quickly implement innovative solutions and respond to emerging opportunities. However, the impulsive nature of spontaneous decision making could also result in a poor AI implementation that lack thorough evaluation and planning.

AI tools can enhance spontaneous decision making by providing actionable insights and data. For instance, AI-driven dashboards and decision support systems can offer immediate feedback, helping spontaneous decision makers to make informed choices even under tight deadlines (Davenport & Ronanki, 2018).

Based on the current literature, we do not have sufficient data to formulate a hypothesis regarding the mediating role of spontaneous decision-making style in the relationship between ethical leadership and AI adoption. Further research is needed to explore how spontaneous decision making interacts with AI adoption in organizational settings. Further, as compared to other decision-making styles, this one appears less relevant, hence, it was excluded from the current investigation also for reasons of parsimony in the questionnaire administration.

3.1.4. Rational Decision Making

Rational decision making involves a systematic, logical approach to analyzing information and evaluating alternatives. This approach is characterized by structured planning and thorough analysis.

This decision-making style is grounded in logical reasoning and empirical data. It follows a step-by-step process of identifying problems, gathering information, evaluating alternatives, and making informed decisions (Scott & Bruce, 1995).

Rational decision making can significantly increase the effectiveness of AI adoption. Leaders who utilize this style are likely to perform detailed cost-benefit analyses and feasibility studies before implementing AI technologies. Moreover, a rational approach helps mitigate the risks associated with AI implementation and ensures that the adopted solutions are truly useful and sustainable (Davenport & Ronanki, 2018).

Based on the evidence from the literature, it is evident that the combination of ethical leadership and a rational decision-making style can positively influence the adoption of AI. This leads us to formulate the following hypothesis H2c:

> "*The positive relationship between ethical leadership and AI adoption is positively mediated by the rational decision-making style*".

If confirmed, this hypothesis would suggest that Rational decision making can enhance the positive effects of ethical leadership on AI adoption,

3.1.5. Dependent Decision Making

The last style, Dependent decision making relies on seeking advice and support from others before making decisions. This style emphasizes knowledge sharing and consensus-building. This decision-making style involves the consultation with others and the reliance on their input to make decisions. It is often observed in individuals who prefer collective decision-making processes and value others' opinions (Scott & Bruce, 1995). Dependent decision makers seek reassurance and validation from peers and superiors before a course of action.

Nowadays, dependent decision making can foster inclusive and well-rounded decisions. Thanks to the engagement of multiple stakeholders in the decision-making process, organizations can ensure that diverse perspectives on various topics are considered (Loo, 2000).

However, this style can also slow down decision-making processes due to the need for extensive consultation. To balance the benefits of collaboration with the need for timely decisions, organizations can establish clear decision-making protocols that facilitate efficient consensus-building.

AI tools can support dependent decision making by providing collaborative platforms and decision support systems that aggregate inputs from various stakeholders. These tools can streamline the consultation process and can make it easier to reach consensus and make informed decisions (Davenport & Ronanki, 2018).

However, based on the current literature, we don't have sufficient information to make hypotheses regarding the mediating role of dependent decision-making style in the relationship between ethical leadership and AI adoption. Further research could be useful to understand how dependent decision-making influences AI adoption in organizational environment. Further, as for the spontaneous decision-making style, given the lower relevance and the need to keep the investigation as parsimonious as possible, this style was excluded from the current study.

3.2. Influence of Leaders' Attitude Towards AI on AI adoption

Logically speaking, the attitudes of leader towards AI is one of the most important aspects to consider determining the extent and success of AI adoption within organizations. Leaders' perceptions and beliefs about AI can significantly influence the organizational culture, employee attitudes, and overall strategic direction regarding AI implementation (Duan et al, 2019).

Obviously, a key factor whose influence on AI adoption should be analyzed is the attitudes of leaders towards AI because it could have a profound impact on both the organizational culture and employee perceptions and adoption of AI. Leaders who exhibit a positive attitude towards AI are likely to foster an environment that encourages innovation and new technology adoption. In contrast, negative attitudes can create resistance and hinder AI integration efforts (Kurup & Gupta, 2022). Emerging trends indicate that leaders are increasingly open to AI, as evidenced by a Gartner survey finding that 79% of corporate strategists consider AI and analytics critical to their success over the next two years (Gartner, 2023). Moreover, according to the EY CEO Outlook Pulse Survey (2023), 67% of CEOs plan to increase their investment in AI and digital technologies over the next 12 months, reflecting a significant shift in leaders' attitudes towards AI adoption. These trends highlight the importance of studying leaders' attitudes towards AI to understand their influence on AI adoption.

Several factors influence the attitudes of leaders towards AI:

1. **Technological Awareness:** Familiarity with AI technologies significantly shape leaders' attitudes. Leaders who understand the capabilities and limitations of AI are more likely to adopt and support AI initiatives (Duan, Edwards, & Dwivedi, 2019). A comprehensive

understanding of AI allows leaders to make informed decisions about integrating these technologies into their operations.

2. **Risk Perception:** Leaders' views on the risks associated with AI, such as data security and job displacement, can affect their willingness to embrace AI. Those who perceive higher risks may be more cautious, while those who see AI as a manageable risk are more likely to adopt it (Kurup & Gupta, 2022). Assessing and mitigating these risks is crucial for fostering a positive attitude towards AI.

3. **Ethical Considerations:** Again, Ethical concerns play a crucial role in shaping attitudes towards AI. Leaders who prioritize ethical leadership are more likely to adopt AI responsibly, ensuring that its implementation aligns with organizational values and societal norms. Previous research suggest that ethical leadership can promote AI adoption by addressing ethical dilemmas and fostering trust within the organization (Tursunbayeva & Chalutz-Ben Gal, 2024).

Positive attitudes towards AI can create a supportive environment for AI initiatives, leading to successful integration and innovation. Leaders who engage in ethical and rational decision-making are better equipped to go through the complexities of AI implementation, balancing technological benefits with ethical considerations (EY CEO Outlook Pulse Survey, 2023). These leaders are adept at incorporating AI into their strategic vision, ensuring that AI-driven changes align with broader organizational goals.

Negative attitudes instead, can lead to resistance and delays in AI adoption. Leaders who are skeptical of AI may obstacle its integration, creating a culture of caution and uncertainty. Furthermore, leaders who are more skeptical about AI often exhibit an avoidant decision-making style, which, according to our previous discussions and formulated hypothesis, contrasts with effective AI adoption. This resistance can slow down technological advancements and reduce the competitive edge of the organization.

Based on the discussions in this paragraph, it is evident that the attitudes of leaders towards AI significantly influence its adoption within organizations. Therefore, we can propose our third hypothesis *H3:*

> *"The positive relationship between ethical leadership and AI adoption is positively mediated by leaders' attitude toward AI."*

Concluding our literature review, we have laid the foundation for our research framework starting with Artificial intelligence, moving through leadership with a deep dive in Ethical Leadership, decision making styles and Technology acceptance. In the next chapter, we will discuss the methodology used to conduct our empirical analysis, including the research design, data collection methods, and analytical techniques.

4. Empirical study

As briefly stated in the previous chapter, this section outlines the methodological framework of this thesis, building on the theoretical foundation established in the literature review. In particular, we have highlighted the complex interaction between ethical leadership, decision-making styles, attitudes toward AI, and artificial intelligence adoption in the work environment. To empirically test the proposed hypotheses and further explore these relationships, a robust research design is needed.

The methodology section will describe the research design, including the survey structure and scales of items developed to capture the shades of ethical leadership, decision-making styles, and attitudes toward AI adoption.

In addition, this chapter will discuss the data analysis techniques used to process and interpret the collected data. These techniques include calculating scale scoring and Z scores to normalize the data, as well as performing regression analyses to examine the direct effect of ethical leadership on AI adoption and the mediating effects of decision styles on the relationship between ethical leadership and AI adoption.

Through this methodological approach, we aim to provide a comprehensive analysis of the factors influencing AI adoption, offering insights into the role of leadership and decision-making in shaping organizational attitudes toward AI.

4.1. Methods

4.1.1. Research Design

The research design was structured around a survey designed to collect quantitative data on various aspects of ethical leadership, decision-making styles, leaders' attitude towards AI and artificial intelligence adoption on the side of employees. This survey serves as the primary tool for validating or not the hypotheses formulated during the literature review, offering a detailed understanding of the dynamics among the key variables identified.

Survey recipients are workers of all ages and sectors who have a supervisor, manager, leader, or boss. This choice allows for a variety of perspectives and captures a diverse range of experiences in different organizational contexts. By engaging employees who regularly interact with leadership figures, we can explore in more depth how perceptions about ethical leadership, leader's attitudes toward AI, and whether leader's decision-making style influence AI adoption from personal and organizational perspectives.

Prior to the administration of the survey, participants were informed about the general scope of the study, treatment of data, and their right to discontinue participation at all times. Hence, in accordance with the Declaration of Helsinki and the APA ethical standards for the treatment of human sample, all participants provided informed consent prior to their participation in the study. The survey consists of six sections, each aimed at exploring a specific aspect of the research. Of these, three sections are based on scales validated in the literature, while the other three were customized to our study context, for a total of 55 items for analysis:

- **Screening Section:** This is the initial and necessary section to ensure that the survey reaches the desired target audience. Two basic questions are administered to participants: the first tests whether the participant has a job, and the second asks whether they have a supervisor, boss, leader, or manager. If a participant answers negatively to either of these questions, the survey stops, as participants profile does not fit the scope of the research. If the answer is yes to both questions, the participant can continue with the survey.
- **Demographic Section:** This section collects demographic information that will serve as control variables in the analysis, such as age, education level, occupational sector, and current position inside the organization. These control variables will allow us to consider how demographic characteristics may influence AI-related perceptions and behaviors, helping to make assumptions and identify limitations in our research.
- **Ethical Leadership:** The third section of the survey is dedicated to measuring ethical leadership through the Ethical Leadership Scale, developed by Yukl, Mahsud, and Prussia (2013). This scale consists of 15 items based on a 7-point Likert scale, which assesses the extent to which leaders demonstrate features of ethical behaviors, such as integrity, fairness, and concern for others, in their decisions and interactions with followers (Yukl et al., 2013). The scale does not consist of subscales and does not include reversed scored, which allows the total scale score to be obtained by simply adding up the various items that make up the scale.
- **Decision Making Styles:** The fourth section of the survey is based on the standardized General Decision-Making Style (GDMS) scale developed by Spicer and Sadler-Smith (2005). This scale is used to measure an individual's general decision-making style and is based on

the assumption that people tend to use one or more preferred styles when making decisions (Spicer & Sadler-Smith, 2005). Originally, the GDMS consists of five subscales, each corresponding to one of the decision-making styles analyzed in the previous chapter: intuitive, rational, avoidant, dependent, and spontaneous. However, to better fit our research context, only three subscales were employed: intuitive, rational and avoidant. This allows us to focus on analyzing the three decision-making styles directly related to the hypotheses formulated earlier.

- *Intuitive Decision-Making:* This subscale consists of 5 items and measures participants' propensity to rely on intuition and instincts when making decisions, emphasizing reliance on personal experiences and immediate reactions.
- *Rational Decision-Making:* This subscale consists of 5 items and assesses participants' systematic and logical approach to decision-making, relying on in-depth analysis and critical evaluation of available information.
- *Avoidant Decision-Making:* This subscale consists of 5 items and detects participants' tendency to avoid or procrastinate decisions, reflecting an attitude of uncertainty or hesitation in decision-making.

The GDMS scale is based on a 5-factor Likert scale, which allows participants to express their degree of agreement or disagreement with each proposed statement. The questions have been customized specifically to study the decision-making style of leaders, ensuring relevance to leadership contexts and the elimination of subscales related to dependent and spontaneous styles is consistent with the purpose of our research, allowing us to focus on the styles most relevant to the hypotheses explored. This simplification also reduces the complexity and burden associated with the process of collecting survey responses. The GDMS scale does not have reverse coded items, which means that the final subscale score can be obtained by simply adding up the individual item scores.

- **Attitude towards AI:** The fifth section of the survey uses the standardized "Attitudes Towards Artificial Intelligence at Work" scale developed by Park, Woo and Kim (2024). This scale is designed to measure workers' attitudes and perceptions about the use of AI in work settings, using 25 items measured on a 7-factor Likert scale. The scale consists of several subscales that explore specific aspects of attitudes toward AI, assessing distinct dimensions of people's perceptions and feelings about integrating AI into work (Park et al., 2024). The scale was tailored to analyze the leader's viewpoint, rather than the respondent's personal viewpoint (i.e., participants were asked to report how much each sentence of the item fits – in their view – their leader's point of view on the matter). In addition, the subscale regarding the humanization of AI was eliminated because of the difficulty for employees to assess their leader's perspective on the issue, as well as to maintain consistency with the specific focus of the research. The subscales used in the survey are:

- *Perceived Quality:* This subscale consists of 5 items and measures perceptions of the quality and reliability of AI, assessing how much participants view AI as an effective means of improving work processes.
- *Anxiety:* Consists of 4 items and assesses the level of anxiety and concern associated with the use of AI, reflecting fears related to the reliability of the technology and its impact on daily work activities.
- *Job Insecurity:* This subscale consists of 4 items and captures the level of perceived job insecurity, examining whether participants fear that AI may threaten their employment stability.
- *Perceived Usefulness:* Consists of 4 items and measures how useful and beneficial participants perceive AI to be in improving work efficiency and effectiveness.

It is important to keep in mind that the subscales inherent in the anxiety and job insecurity constructs include reverse items. This means that in calculating overall attitude, the scores on these scales should be reversed, since higher levels of anxiety and job insecurity are associated with lower adoption of AI in the organizational environment.

- **AI adoption:** The final section of the survey concerned AI adoption within the organization and by the individual respondent. This section, although brief, is crucial to our study, as it constitutes the dependent variable of our research model. It is not based on a scale validated in the literature but uses two key questions to collect data on perceptions of AI adoption. The first question is about AI adoption on a personal level, asking respondents how much they use AI in their daily work. The second question explores AI adoption at the organizational level, investigating respondents' perceptions of the overall integration of AI in their organization. These questions provide insight into how the independent variables, derived from the scales in the previous sections, influence AI adoption.

In conclusion, the survey is designed to provide a detailed and quantifiable picture of the relationships between ethical leadership, decision-making styles, leaders' attitude toward AI and AI adoption. The data collected through these sections will allow us to explore the dynamics that drive AI adoption in modern organizations. In the next section, the data analysis techniques used to interpret the survey results and test the hypotheses developed will be discussed.

4.1.2. Data analysis techniques

The first step in the data analysis process is to calculate the scores of the different scales used in the survey. Each survey response is transformed into a score based on Likert scales, which are used to measure participants' perceptions and attitudes. To ensure consistency in the analysis, the second step is to convert the scale scores into z-scores. The transformation of scores into z-scores allows for a distribution of scores with a mean of 0 and a standard deviation of 1. The z-scores express how far a respondent's score deviates from the sample mean in terms of standard deviation, facilitating comparative analysis and allowing more precise assessment of variables.

Before conducting the actual statistical testing, each scale and subscale was subject to a reliability analysis in order to ensure that all variables were valid. In this analysis we employed the standard calculation of the Cronbach's Alpha.

In the analysis, we aim to test a conceptual model that explores the impact of ethical leadership on AI adoption within organizations. The model is depicted in the figure below *(see Figure 2)*, where X represents our independent variable, Ethical Leadership, and Y represents the dependent variable, AI Adoption. The model is structured to examine both the direct effect of ethical leadership on AI adoption and the indirect effects mediated by leaders' decision-making (M1) styles and attitudes toward AI (M2).

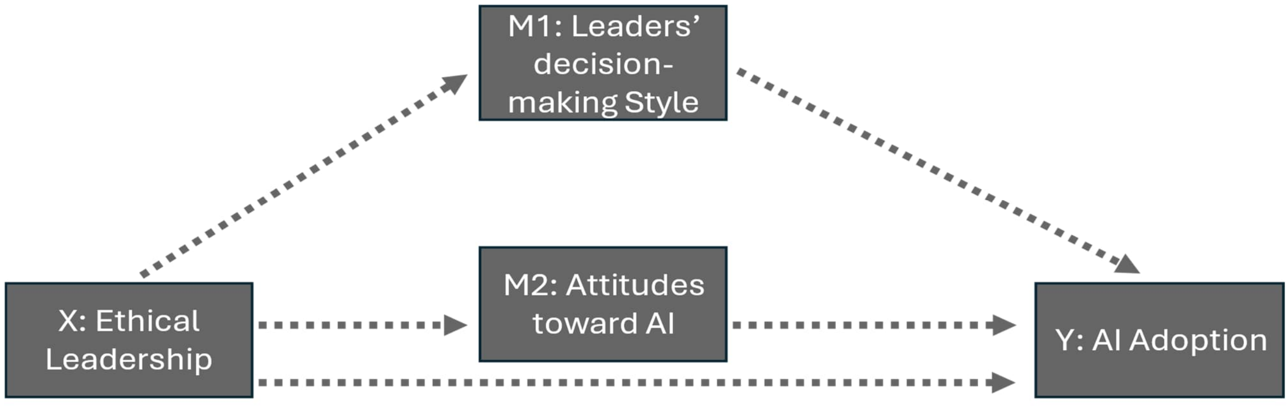

Figure 2: Theoretical framework.

The model is organized as follows:

- Direct Path (X → Y): The direct relationship between ethical leadership and AI adoption is represented by the lower arrow. This relationship corresponds to our first hypothesis (H1), which will be tested using multiple linear regression. This model will allow the analysis of the direct relationship between the score on the ethical leadership scale and the level of AI adoption. Linear multiple regression will be used to determine the magnitude and direction of the relationship, providing a regression coefficient indicating the expected impact of ethical leadership on AI adoption. In particular, in this analysis, the AI adoption scale has been used as a dependent variable, and the ethical leadership score as independent variable, along with a series of control variables, namely: gender, age, education, industry and leader seniority.
- Mediated Pathways (X → M1 → Y and X → M2 → Y): The model also explores the potential mediating roles of decision-making styles, represented by M1, and Leaders' attitude toward AI, represented by M2. Specifically, M1 includes three distinct decision-making styles: Intuitive, Avoidant, and Rational. Each of these styles is hypothesized to mediate (positively, or negatively) the relationship between ethical leadership and AI adoption. As mentioned before, these mediations correspond to our hypotheses H2a, H2b, and H2c.
  The second mediator M2, representing the leader's Attitude toward AI, is hypothesized to positively mediate the relationship between ethical leadership and AI adoption (H3).

In order to test hypotheses H2a, H2b, H2c, and H3, a series of mediation models have been conducted using the PROCESS macro for SPSS. The models will allow not only to assess the direct effect of ethical leadership on AI adoption, but also to understand how decision-making styles and attitudes toward AI can mediate this relationship. In particular four models were conducted using the AI adoption score as dependent variable, the ethical leadership score as independent variable, and the decision-making styles (intuitive, rational and avoidant) as first mediator (M1) and leader's attitude toward AI score as second mediator (M2); because decision making style includes three possible styles, each of the scales was used as mediator in a separate analysis. Finally, all analysis were run including a series of covariates, namely, gender, age, education, industry and leader's seniority.

4.2. Empirical Findings

This paragraph presents the empirical results from the analysis of the data collected through the survey described in the previous one. The goal is to provide an in-depth view of the sample characteristics, descriptive statistics, and data reliability, and then proceed to test the research hypotheses using regression and mediation analysis.

4.2.1. Sample Characteristics and Descriptive statics

A total of 151 participants took part in the study. However, 46 participants have been excluded for one of two possible reasons. First, they did not conclude the entire set of questions of the survey, hence, their data were incomplete; second, they answered “no” to one of the two screening questions, hence, they were not representative of the sample under investigation. The final sample included a total of 97 valid responses (mean age: 26 ± 6.5 years).

The sample includes participants from a variety of demographic and professional backgrounds, ensuring adequate and diversified representativeness for analysis.

Starting with the gender distribution (*see Figure 3*), the sample shows a diverse distribution, with a majority of male participants (57 %), followed by a significant female representation (41 %). Only a very small percentage chose options such as “non-binary” or “I prefer not to answer.” This gender distribution could be relevant in identifying which gender is more likely to adopt AI within an ethical leadership context, contributing to a deeper understanding of the dynamics of technology adoption under an ethical guidance.

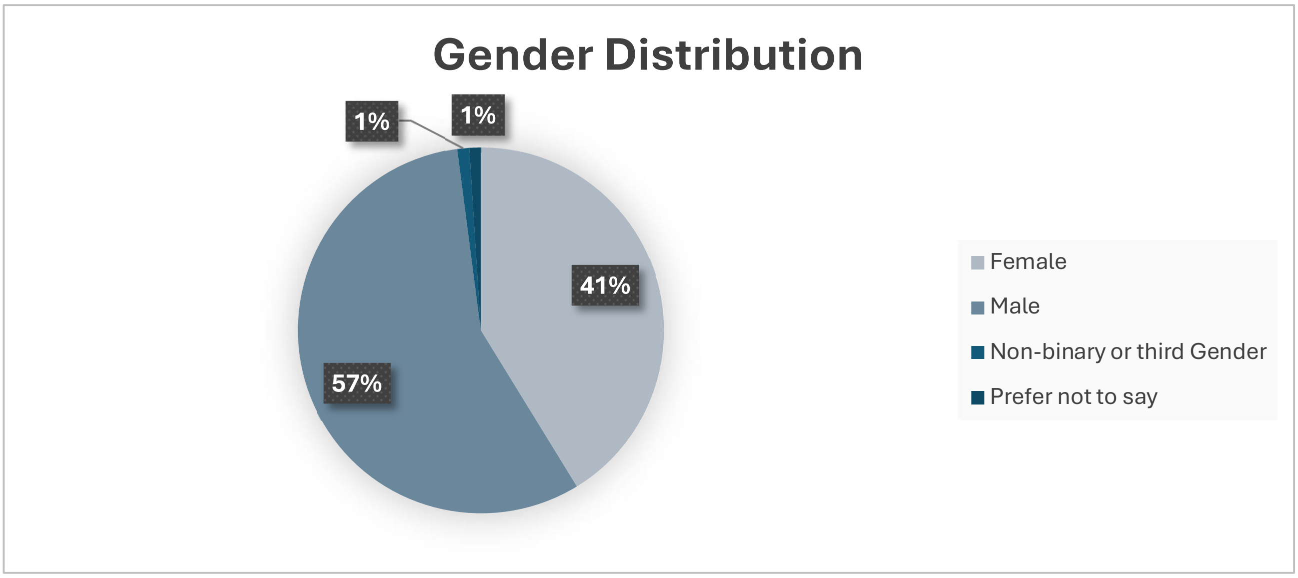

Figure 3: Sample Gender Distribution

As for the level of education (*see Figure 4)*, participants show a high standard of education, with the majority holding a master's degree (54%). This is followed by those who hold a bachelor's degree

(32%), while only a minority have a level of education equivalent to a high school diploma (10%) or doctorate (4%).

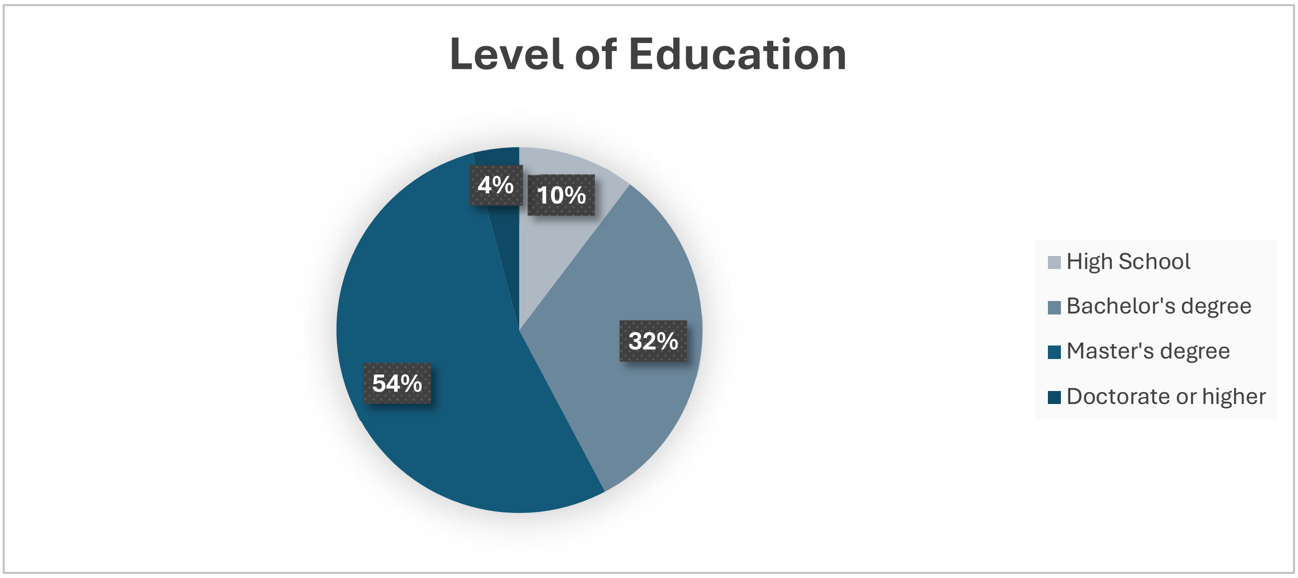

Figure 4: Sample Level of Education

However, in terms of sector *(see Figure 5)*, the sample is predominantly composed of participants working in the tertiary sector, with a percentage of 94%. This is followed by 5% of participants in the secondary sector, while the armed forces sectors constitute a minority, accounting for 1% of the total sample. This predominance of the tertiary sector could be seen as a limitation, as the sample may not be fully representative of all industries, and as a result, conclusions regarding AI adoption may be more applicable to tertiary contexts, where AI adoption is generally more rapid and widespread, than to other, less represented sectors.

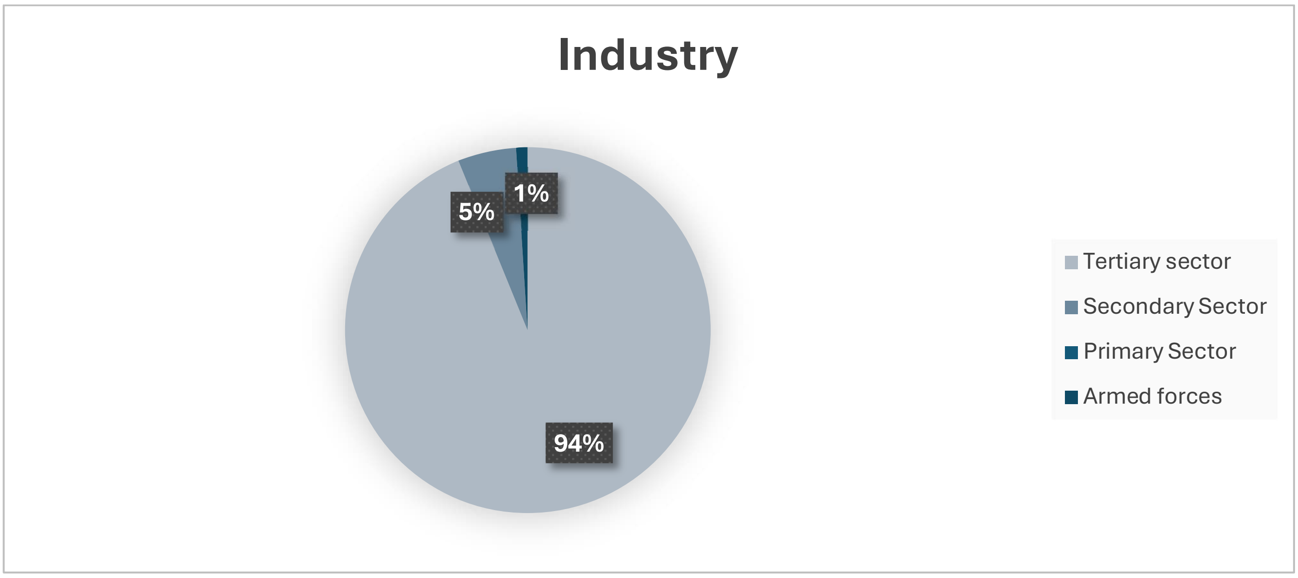

Figure 5: Sample Industry Distribution

Another aspect of key importance is the seniority of the leader *(see Figure 6)*. Regarding leader seniority, the sample is mainly composed of individuals reporting to leaders in middle management positions (66%), followed by those with leaders in top management positions (34%). This finding is particularly relevant because the leader's level of seniority could have a significant influence on the perception of ethical leadership and the propensity for AI adoption within organizations. In addition, defining to which level the supervising leader belongs could be relevant in understanding whether the relationship between ethical leadership, decision making style, and AI adoption is applicable to all levels of the organizations' hierarchy or only to certain levels.

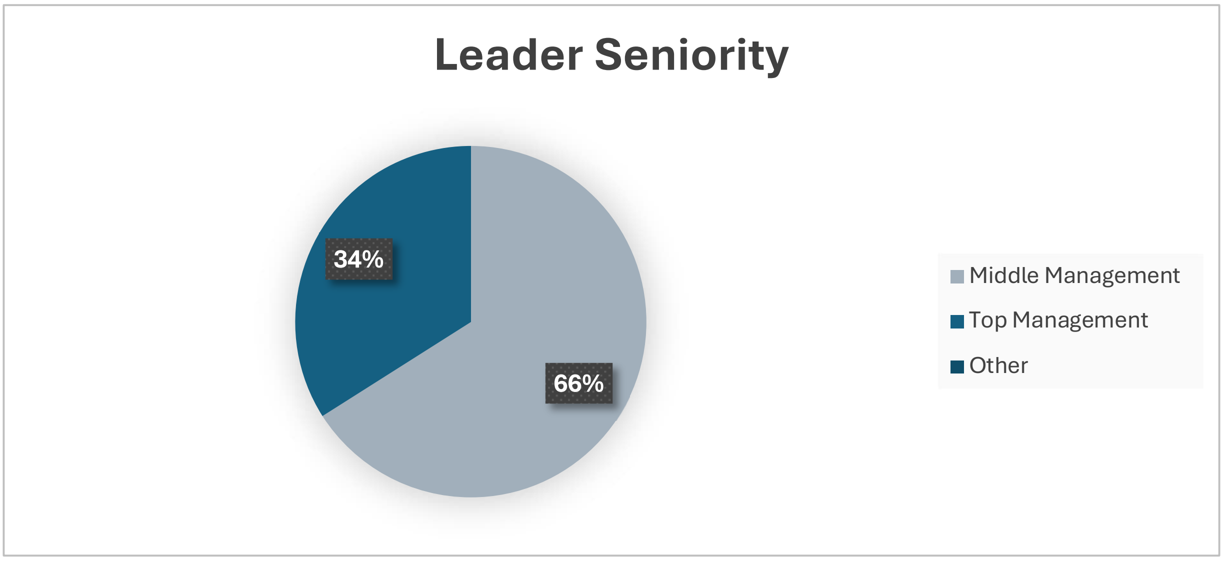

Figure 6: Sample Leader Seniority Distribution

Finally, the majority of participants hold intern or junior positions *(see figure 7)*. These positions and similar roles make up about 70% of the total sample. In contrast, a smaller percentage of the sample consists of individuals in managerial or senior positions, such as Managers and Senior Consultants. These participants represent about 20% of the sample. Another significant category, although less represented, includes technical and specialized roles such as IT Developer, Banking Consultant, Medical Specialist, and Wealth Advisor, which make up about 10% of the sample.

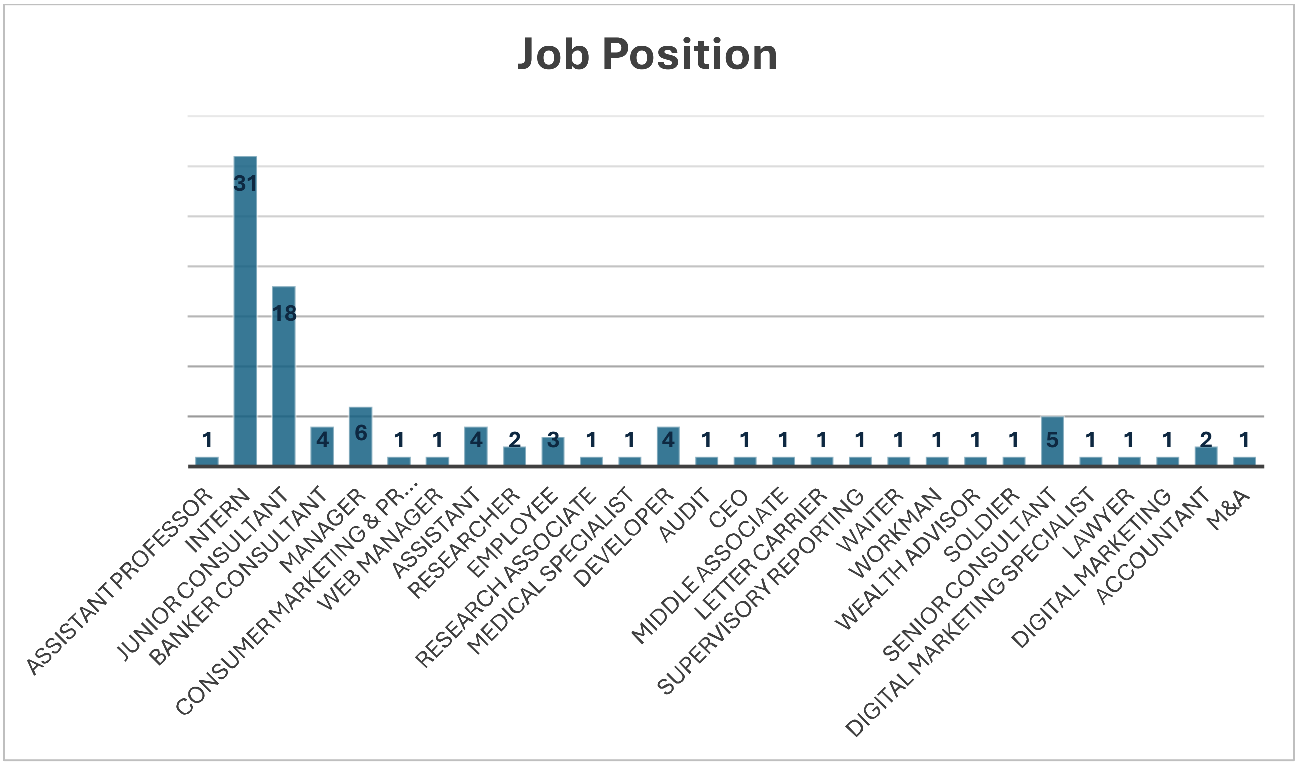

Figure 7: Sample Job Position Distribution

Turning the focus now to descriptive statistics, they provide an essential overview of the key variables collected in the survey, offering a first picture of the main characteristics of the sample. Table 1 summarizes the main descriptive measures. By analysing the mean, standard deviation, and minimum and maximum values of each of the raw scores associated with each scale in the survey, it is possible to identify general trends, variations, and potential outliers in the data. These statistics are a key step in understanding the distribution of the data within the sample thus preparing the ground for a more in-depth discussion of the implications and insights from the data analysis.

Table 1: Descriptive Statics.

Descriptive Statics					
	N	Minimum	Maximum	Mean	Std. Deviation
Ethical Leadership	97	22	98	80.07	16.678
Intuitive Decision Making Style	97	10	25	18.82	3.272
Rational Decision Making Style	97	11	25	21.67	3.155
Avoidant Decision Making Style	97	5	24	9.12	4.510
AI Perceived Quality	97	5	35	25.15	6.995
AI Anxiety	97	4	28	10.20	5.351
AI Job Insecurity	97	3	21	7.88	3.954
AI Perceived Utility	97	4	28	19.93	4.861
AI Attitude (Total score)	97	50	117	88.36	15.398
AI Adoption	97	2	14	11.18	3.000

4.2.2. Scales Reliability

Data reliability is a crucial element in empirical research, as it ensures that measurement instruments are consistent and produce stable results over time. To assess the internal consistency of the scales used in our survey, we checked reliability by calculating Cronbach's alpha coefficient.

Cronbach's alpha is a statistical tool employed to assess the reliability or internal consistency of a set of items inside a scale (Cronbach, 1951). In simple terms, Cronbach's alpha verifies that survey respondents answer questions consistently over time by not contradicting themselves across items. Cronbach's alpha values go from 0 to 1, with higher alpha values highlighting stronger internal consistency. Generally, an alpha value above 0.70 is considered acceptable, while values above 0.80 indicate good reliability.

In the case of our analysis, all scales used showed Cronbach's alpha values above the threshold of 0.70, showing a high level of reliability. Following there are the specific values obtained for each scale: ethical leadership showed a Cronbach's alpha value of 0.961, suggesting very high internal consistency among its 14 items; the General Decision-Making Style (GDMS) scale was analyzed separately for the three subscales of interest: the subscale measuring intuitive decision-making style obtained a Cronbach's alpha value of 0.785, rational decision-making style showed a value of 0.845, and lastly, the subscale related to avoidant decision-making style showed an alpha value of 0.900.

The scale related to attitude toward artificial intelligence was divided into four subscales, each of which showed high reliability values: perceived quality of AI obtained a Cronbach's alpha of 0.931, anxiety associated with AI use showed a value of 0.893, while the subscale measuring perceived job insecurity recorded an alpha of 0.903, finally, the subscale assessing perceived usefulness of AI obtained a Cronbach's alpha value of 0.852. The overall score for attitude toward AI, obtained from the sum of the different subscales, showed a Cronbach's alpha value of 0.887, confirming the overall reliability of the scale.

Conclusively, the results of the reliability analyses indicate that all scales used in the survey are highly reliable and provide a solid basis for subsequent analyses. The robustness of the data collected through these scales reinforces the validity of the results that will emerge from the regression analysis that will be conducted in the next paragraph.

4.2.3. Hypothesis testing

The results of the multiple linear regression analysis conducted to test our first hypothesis (H1) are summarized in Table 2.

Table 2: Linear Regression analysis - Coefficients (H1). Outcome Variable: AI Adoption

	Unstandardized Coefficients		**Standardized Coefficients**		
	β	**Standard Error**	**β**	**t**	**p**
Ethical Leadership	0.481	0.090	0.481	5.337	0.000
Leader Seniority	-0.217	0.197	-0.103	-1.101	0.274
Age	-0.009	0.015	-0.056	-0.583	0.561
Gender	0.334	0.158	0.190	2.118	0.037
Education	0.084	0.126	0.062	0.670	0.504
Industry	0.317	0.365	0.078	0.870	0.387

The regression model was overall significant ($F_{6, 96} = 6.193$ $p < 0.001$). In particular, examining the standardized coefficients, ethical leadership has a significant positive impact on AI adoption ($\beta = 0.481$, $t = 5.337$, $p < 0.001$). This result confirms our first hypothesis (H1) that greater ethical leadership is associated with greater adoption of AI in organizations.

In addition, among the covariates included in the model, the gender variable was also found significant ($\beta = 0.190$, $t = 2.118$, $p = 0.037$). Specifically, male gender is associated with greater propensity toward AI adoption than female gender. This suggests that, within the sample analyzed, men are more likely than women to favor the integration of AI into business practices.

The other covariates, including age, education level, leader seniority, and industry, do not show statistically significant effects on AI adoption within this model, as indicated by relative p-values greater than 0.05 (see table 2 for detailed results).

Hypotheses H2 (a, b and c) and H3 have been tested using a series of three mediation analysis run in the PROCESS macro for SPSS.

The first model (H2a, H3) explores how the independent variable (Ethical Leadership) affects the dependent variable (Adoption of AI) through the mediated effect of two other variables: intuitive decision-making style (M1) and leader's attitude toward AI (M2).

The control variables used in this analysis are the same as those employed in the multiple linear regression: leader's seniority, age, gender, education level, and industry sector.

The results indicates that the model was overall significant ($R = 0.70$, $R^2 = 0.49$, $F_{7, 89} = 12.02$, $p < 0.001$). In particular, the direct effect of Ethical Leadership was found to be non-significant ($\beta = 0.11$, $p = 0.26$), along with the direct effect of intuitive decision-making style ($\beta = -0.09$, $p = 0.27$). Conversely, the direct effect of AI attitude was found to be significant ($\beta = 0.58$, $p = 0.00$). As for the covariates, none was found to exert a statistically significant effect (see Table 3 for detailed results).

Table 3: Mediation Model 1 (Intuitive). Outcome Variable: AI Adoption.

Direct Effects						
	B	**SE**	**t**	**p**	**LLCI**	**ULCI**
Ethical Leadership	0.11	0.10	1.13	0.26	-0.08	0.31
Intuitive Decision Making	-0.09	0.08	-1.12	0.27	-0.24	0.07
AI Attittude	0.58	0.10	5.84	0.00	0.38	0.77
Leader Seniority	-0.14	0.17	-0.83	0.41	-0.48	0.20
Age	-0.01	0.01	-0.95	0.34	-0.04	0.01
Gender	0.18	0.14	1.27	0.21	-0.10	0.45
Education	0.08	0.11	0.75	0.46	-0.13	0.29
Indirect Effects						
	β	**SE**	**t**	**p**	**LLCI**	**ULCI**
TOTAL	0.36	0.10	-	-	0.20	0.57
Intuitive Decision Making	0.01	0.02	-	-	-0.01	0.06
AI Attitude	0.35	0.09	-	-	0.19	0.55

With respect to the indirect effects, the one of the intuitive decision-making style failed to reach statistical significance (β =0.01, LLCI = -0.01, ULCI = 0.06), hence, leading to rejection of hypothesis H2a. On the other hand, the indirect effect of AI attitude was fund statistically significant (β =0.35, LLCI = 0.19, ULCI = 0.55), hence, confirming H3.

The second model (H2b, H3), on the other hand, examines the influence of the independent variable (Ethical Leadership) on the dependent variable (Adoption of AI) while considering this time the mediated effect of: the avoidant decision-making style (M1) and the leaders' attitude toward AI (M2). The control variables remain the same as those used in the previous model: leader seniority, age, gender, education level, and industry sector.

The results show that the overall model is significant ($R = 0.77$, $R^2 = 0.60$, $F_{7, 89} = 18.73$, $p < 0.001$). In particular, the direct effect of Ethical Leadership was significant (β = 0.18, p = 0.04), as was the positive direct effect of avoidant decision-making style (β = 0.48, p = 0.00) and attitude toward AI (β

= 0.87, p = 0.00). As for the covariates, none of them showed a statistically significant effect on the model (see Table 4 for detailed results).

Table 4: Mediation Model 2 (Avoidant). Outcome Variable: AI Adoption.

Direct Effects						
	B	**SE**	**t**	**p**	**LLCI**	**ULCI**
Ethical Leadership	0.18	0.09	2.04	0.04	0.00	0.35
Avoidant Decision Making	0.48	0.09	5.07	0.00	0.29	0.66
AI Attittude	0.87	0.11	8,24	0.00	0.66	1.08
Leader Seniority	-0.08	0.15	-0.52	0.61	-0.38	0.22
Age	-0.01	0.01	-0.87	0.39	-0.03	0.01
Gender	0.07	0.12	0.57	0.57	-0.18	0.32
Education	0.01	0.10	0.15	0.88	-0.18	0.21
Indirect Effects						
	β	**SE**	**t**	**p**	**LLCI**	**ULCI**
TOTAL	0.30	0.07	-	-	0.16	0.45
Avoidant Decision Making	-0.23	0.06	-	-	-0.35	-0.10
AI Attitude	0.53	0.09	-	-	0.35	0.71

Regarding the indirect effects, the one related to avoidant decision style reached statistical significance (β = -0.23, LLCI = -0.35, ULCI = -0.10); despite the direct effect of the avoidant decision-making style was surprisingly found positive, the direction of the indirect effect is instead negative, in line our initial hypothesis suggesting a negative effect on AI adoption, hypothesis H2b is accepted. These results overall highlight a possible anomaly or unanticipated dynamic, suggesting the need for further research to explore more fully the role of avoidant decision-making style in AI adoption. On the other hand, the indirect effect related to attitude toward AI was found to be statistically significant (β = 0.53, LLCI = 0.35, ULCI = 0.71), again confirming the H3 hypothesis.

The third and final model (H2c, H3) analyzes the influence of the independent variable (Ethical Leadership) on the dependent variable (AI Adoption) through the mediated effect of two key variables: rational decision-making style (M1) and leaders' attitude toward AI (M2). The control variables used in this model are the same as those used in the previous models: leader seniority, age, gender, education level and industry sector.

The results indicate that the model was significant overall ($R = 0.69$, $R^2 = 0.48$, $F_{7, 89} = 11.77$, $p < 0.001$). Specifically, the direct effect of ethical leadership was not significant ($\beta = 0.10$, $p = 0.37$), as was the direct effect of rational decision-making style ($\beta = 0.06$, $p = 0.57$). In contrast, again the direct effect of attitude toward AI was significant ($\beta = 0.55$, $p = 0.00$). As for the control variables, none of them showed a statistically significant effect (see Table 5 for detailed results), in line with the previous analyses.

Table 5: Mediation Model 3 (Rational). Outcome Variable: AI Adoption.

Direct Effects						
	B	**SE**	**t**	**p**	**LLCI**	**ULCI**
Ethical Leadership	0.10	0.11	0.89	0.37	-0.12	0.32
Rational Decision Making	0.06	0.11	0.56	0.57	-0.16	0.28
AI Attittude	0.55	0.10	5.29	0.00	0.34	0.76
Leader Seniority	-0.13	0.17	-0.76	0.45	-0.47	0.21
Age	-0.01	0.01	-1.03	0.30	-0.04	0.01
Gender	0.16	0.14	1.17	0.24	-0.11	0.44
Education	0.06	0.11	0.57	0.57	-0.16	0.28
Indirect Effects						
	β	**SE**	**t**	**p**	**LLCI**	**ULCI**
TOTAL	0.37	0.14	-	-	0.16	0.68
Rational Decision Making	0.04	0.11	-	-	-0.12	0.32
AI Attitude	0.34	0.09	-	-	0.17	0.53

Concerning indirect effects, the one related to rational decision-making style did not reach statistical significance ($\beta = 0.04$, $LLCI = -0.12$, $ULCI = 0.32$), thus leading to the rejection of the hypothesis

H2c. On the other hand, the indirect effect of leaders' attitude toward AI was significant ($\beta = 0.34$, LLCI = 0.17, ULCI = 0.53), thus confirming hypothesis H3.

To conclude, the analysis of the results largely confirmed the hypotheses made, highlighting how ethical leadership plays a crucial role in influencing both the decision-making style of leaders and their attitude toward AI adoption. Although some results were unexpected, such as the positive direct effect of avoidant decision-making style on AI adoption, these can be found in further discussion in the following chapter.

5. Discussion and Conclusions

Based on the results obtained from our empirical analyses, it is time to reflect on these findings and integrate them into a broader context, considering the existing literature and the theories that guided this research. The previous chapter highlighted how ethical leadership directly and indirectly influences AI adoption in organizations, through various decision-making styles and leaders' attitudes toward AI. Now, in this final chapter, we aim to take a step back to provide an overview, summarizing the main findings that emerged and interpreting them in light of the initial hypotheses and theories examined.

To begin, we will summarize and interpret the key findings, highlighting how they relate to theoretical expectations and contributions in the literature. Next, we will discuss the practical implications of these findings for organizational leadership and management, exploring how organizations can apply these insights to improve their AI adoption strategy. In addition, we will explore how our study fits into the existing research landscape, helping to fill in some of the gaps and propose new perspectives for the study of leadership in the AI era.

Finally, we will acknowledge the limitations of our study, discussing the factors that may have influenced the results and offering suggestions for future research that can expand and deepen the topics covered. This chapter aims, therefore, not only to close the circle of our research, but also to open new avenues for further exploration in this dynamic and ever-evolving field.

5.1. Summary and Interpretation of Key findings

First, the current study confirmed the initial hypothesis (H1), which assumed a positive effect of ethical leadership on AI adoption. The results of multiple linear regression clearly indicate that leaders who practice ethical leadership are more likely to adopt AI in their organizations. This result is in line with previous literature, which shows that ethical leadership creates an organizational climate that fosters innovation, experimentation, and adoption of new technologies (Shafique et al., 2020). Ethical leadership, through the promotion of values such as integrity, transparency, and fairness, can mitigate internal resistance and build an environment of trust necessary for embracing and implementing complex technologies such as AI.

The confirmation of this hypothesis not only reinforces the theory that ethical leadership is a facilitator for AI adoption, but also suggests that organizations wishing to integrate effectively with AI should invest in the development of ethical leadership features. However, it is important to consider that the impact of ethical leadership on AI adoption could vary depending on several contextual factors, such as the organization's technological maturity, company culture, and resource availability. This emphasizes the importance of adapting leadership practices to the organization's specific context to maximize the benefits of AI adoption.

The second set of hypotheses explored the role of different decision-making styles as mediators in the relationship between ethical leadership and AI adoption. Hypothesis H2a, which proposed that intuitive decision-making style might positively mediate this relationship, found no empirical support. This might indicate that although intuition is a crucial component in many managerial decisions, it does not play a significant role when it comes to adopting advanced technologies such as AI, which, according to the literature, often require a more rational, data-driven approach (Duan et al., 2019).

The absence of a significant effect of intuitive decision-making style might suggest that AI adoption requires more structured and analytical decisions. In highly technological contexts, intuition may not be sufficient to deal with the complexities and long-term implications associated with AI integration. This result may also reflect the need for more training and technical expertise among leaders so that they can make informed decisions about AI adoption.

Hypothesis H2b, which instead explored the role of avoidant decision-making style, produced unexpected results. Although the analysis showed that ethical leadership reduces the tendency to use an avoidant style, the avoidant style still showed a positive direct effect on AI adoption. Nonetheless, the indirect effects, on the other hand, showed a negative effect. Despite H2b being confirmed by the analyses, its co-existence with a positive direct effect appears odd and counterintuitive as it seems to contradict the existing literature, which associates avoidant style with a tendency to avoid difficult, complex decisions and innovation (Davenport & Ronanki, 2018).

This result raises significant questions and could suggest that in contexts of high complexity or uncertainty, leaders who tend to avoid difficult decisions may end up adopting AI as a kind of last option solution, or they may find it a good resource to reduce uncertainty. However, this result could also be an anomaly due to methodological limitations, such as insufficient statistical power or specificity of the sample analyzed. This point requires further investigation, which will be discussed in more detail in the following sections on the limitations of the study.

In conclusion of the second set of hypotheses, hypothesis H2c, related to rational decision-making style, the results indicate that rational style did not emerge as a significant mediator in the relationship between ethical leadership and AI adoption.

The fact that rational decision-making style does not significantly mediate AI adoption may indicate that although ethical leaders favor decisions based on thorough and reasoned analysis, other factors, such as overall attitude toward AI, or other variables not included in the analysis, carry more weight in determining the actual adoption of the technology. This result suggests that in order to promote AI adoption, it is not enough just to adopt a rational decision-making approach; it is also critical that leaders develop a positive and confident attitude toward AI.

Turning to the interpretation of the last hypothesis, leaders' attitudes toward AI proved to be the strongest and most significant mediator in the relationship between ethical leadership and AI adoption, confirming hypothesis H3. Importantly, the leader’s attitude toward AI appeared to have both a direct effect on the AI adoption, as well as to positively mediate the relationship between ethical leadership and AI adoption. This result highlights the importance of leaders' mindset and perceptions in the adoption of new technologies. Leaders who develop a positive view of AI, seeing it as an opportunity rather than a threat, are the ones who are likely to successfully drive AI adoption across employees in their organizations.

This finding underscores the crucial importance of working on the mindset and vision of leaders to promote AI adoption. Positive perceptions of AI, facilitated by ethical leadership, can act as a catalyst for overcoming resistance to change and encouraging broader and deeper integration of technology. This suggests that organizations should invest not only in technical training, but also in leadership development programs that emphasize the importance of an open and proactive mindset toward innovation and new technologies.

In short, the results of our analysis provide a more refined and complex understanding of the dynamics influencing AI adoption in organizations. While some findings confirmed our initial hypotheses and align with the existing literature, others raised new questions and areas of uncertainty that warrant further exploration.

5.2. Implications for Leadership and Organizational Management

The advent of artificial intelligence in organizations is redefining the very concept of leadership. The results of this study not only validate some of our initial hypotheses, but also open new perspectives on how leaders should operate in a world increasingly dominated by emerging technologies. The resulting implications offer significant insights for those leading organizations, providing a road map for successfully navigating the challenges and opportunities presented by AI.

The leader of the future, or rather, the leader of today, cannot simply follow traditional leadership models. Our findings underscore that a combination of ethical qualities, decision-making skills, and a positive attitude toward innovation is required to effectively lead AI adoption. Ethical leadership emerges as a key pillar. It is not just about acting with integrity and transparency, but about creating an environment in which trust becomes the driver of innovation. In a world where AI can inspire fear and resistance, a leader's ability to build an environment of trust is crucial to overcoming barriers to change.

Our analysis highlights how leaders who practice ethical leadership not only facilitate AI adoption but do so in a way that is perceived as right and responsible by their teams. This ethical approach is not only a moral choice, but also a practical strategy for navigating the complexities associated with the introduction of modern technologies. A leader who promotes ethical values can reduce AI-related anxiety and concerns, making the technology integration process smoother.

In addition to ethics, a positive attitude toward AI is likewise vital. Our study showed that the attitude of leaders is the most significant mediator in the relationship between ethical leadership and AI adoption. Further, it also exerts a direct effect on AI adoption. This suggests that it is not enough for a leader to be technically competent; they must also have a clear vision of the role that AI can play in organizational innovation. Leaders who see AI as an opportunity rather than a threat are those who most successfully drive adoption of these technologies. In an environment where the speed of technological change is unprecedented, a leader's ability to maintain a proactive and forward-looking attitude becomes a key element for success.

Finally, although the results of our study do not directly support the mediation of rational decision-making style in the adoption of AI, the literature suggests that the ability to balance rational decisions with strategic insights nevertheless remains important (Duan et al., 2019). In contexts of high uncertainty and complexity, such as AI, intuition can provide leaders with a competitive advantage, but it is rationality that ensures that decisions are well thought out and sustainable. This interplay between intuition and rationality reflects the need for a new kind of leader who can navigate between rigorous analysis and creative innovation.

Shifting the focus now to organizational impacts, ethical leadership not only influences AI adoption, but has a profound impact on the broader organizational context. An ethical leader is able to shape corporate culture, creating an environment that values innovation, continuous learning, and experimentation. In a world where AI is rapidly transforming business models, leaders must be able to instil in their organizations a culture of adaptability and resilience. An organization's ability to evolve and embrace new technologies depends largely on the culture the leader is able to create.

This leads us to consider the importance of change management. Adoption of AI is not a linear process; it requires careful management of resistance and internal dynamics. Ethical leaders are particularly effective in minimizing resistance to change because they are able to address employee concerns in a transparent and accountable manner. An ethical approach to change management not only facilitates the adoption of AI, but also strengthens the bond between the leader and their employees, creating a climate of collaboration and trust.

Another key implication concerns leadership training and development. In the AI era, leaders must possess a much broader skill set than in the past. As mentioned earlier, it is not enough to have a solid technical foundation; leaders must also be able to manage the ethical and social implications of AI adoption. Training programs for leaders should therefore be geared not only toward developing technical skills, but also toward promoting ethical leadership features and the ability to manage change. Investing in this type of training is crucial to preparing leaders to navigate the complexities of AI adoption and to ensure that organizations can thrive in a changing environment.

Regarding organizational governance, organizations that aim to integrate AI in an ethical and sustainable manner must develop governance policies that reflect the principles of ethical leadership. This means creating clear and rigorous guidelines for the use of AI that ensure transparency, accountability, and respect for all the organization’s stakeholders. Ethical leaders, as evidenced by our results, are uniquely positioned to ensure that these policies are not only implemented, but also respected and valued within the organization. AI governance is not just about regulatory compliance, but also about building a corporate reputation based on integrity and trust.

In addition, AI implementation strategies must be thought of holistically. This involves not only fostering a positive attitude toward AI among leaders, but also ensuring that AI implementation is aligned with the organization's ethical values. A practice that organizations should consider is including internal forums where employees can voice their concerns and contribute to the decision-making process regarding AI adoption. Creating a space for open and transparent dialogue is essential for addressing ethical and operational challenges related to the adoption of recent technologies.

In conclusion, the implications for leadership and management that emerged from this study are profound and insightful. An approach based on ethical leadership and proactive change management not only facilitates the adoption of AI, but also promotes a corporate culture that values innovation, integrity, and sustainability. These insights provide a solid foundation on which to build effective leadership strategies in the AI era. Consequently, it is critical to reflect on how these findings help fill gaps in the existing literature.

5.3. Contribution to existing literature

This thesis is a significant and innovative contribution to the existing literature, addressing a topic of extraordinary relevance and importance: the integration of artificial intelligence within organizations. Although AI has been the subject of numerous studies and research, until now there has been a lack of comprehensive analysis that directly links leadership and decision-making with AI adoption. This paper fits into that gap, providing a new and integrated perspective that explores how ethical leadership and decision-making styles can crucially influence the adoption of advanced technologies such as AI.

The relevance of this study lies not only in its subject matter, but also in the historical and social context in which it is set. AI has become a central issue in contemporary debates, not only in the field of technology, but also in the fields of business management, ethics, and governance. However, despite the growing interest in AI, the link between leadership, decision-making and AI adoption has remained relatively unexplored. The existing literature has often treated these areas separately, failing to offer a holistic view that highlights their interconnections.

Our study stands out for addressing this gap by showing that ethical leadership is not only a key element in managing human resources or creating a healthy work environment, but that it also plays a crucial role in guiding AI adoption. Through a detailed empirical analysis, we showed how leaders who embody ethical principles can positively influence decisions about AI implementation, promoting more informed and responsible adoption of these technologies.

To conclude, the present analysis not only fills a gap in the literature but also enriches the academic and practical debate with new insights that are critical to understanding and managing the integration of AI in modern organizations. This contribution is particularly significant at a time when the ability to adopt and manage AI ethically and strategically can determine the success or failure of organizations.

5.4. Limitations of the study and Suggestions for Future Research

Every study has limitations that affect the generalizability and applicability of its results, and this thesis is not an exception. The first significant limitation concerns the composition of the sample, which consists almost entirely of individuals employed in the tertiary sector. While this sector is particularly relevant for the implementation of AI, the results obtained can hardly be extended to other sectors, such as the secondary or primary sector, where the organizational dynamics and challenges associated with AI implementation might be substantially different. For future research, it would therefore be desirable to include a more diversified sample representing a wider range of sectors to see if the relationships identified in this study can be applied in other contexts as well.

Another significant limitation is the distribution of job positions within the sample. Most participants are in junior or intern level positions, which could suggest that the results are particularly relevant only to early career phases or to those individuals at the lower levels of the organizational hierarchy. This may reduce the ability to generalize the results to middle or top management positions, where the dynamics of leadership and decision-making may differ significantly. For example, in the case of early career workers, the influence of leaders and their attitudes toward technology adoption may be magnified compared to more senior employees; this may be due to the need of guidance for career development that distinguishes such employees, who may consequently be more susceptible to leaders' influence and attitudes. Therefore, future research should include a more balanced sample in terms of seniority to explore whether and how ethics in leadership, decision-making styles, and leaders' attitudes influence AI adoption at different organizational levels.

The last crucial limitation concerns the statistical power of the study. Although the sample of 97 respondents provided useful data to test the proposed model, a larger sample could have increased the robustness of the results and provided greater statistical certainty. This issue is particularly relevant to interpreting the unexpected result regarding avoidant decision-making style, which, contrary to expectations, showed a positive direct effect on AI adoption, along with an indirect negative one. This result could be due to a statistical error or sample anomaly, suggesting the need to replicate the study with a larger sample to verify the validity of this result and eventually correct this inconsistency.

Based on the identified limitations, several directions emerge for future research. A natural first direction would be, as mentioned when listing the limitations, to replicate the study with a larger and more varied sample, both in terms of economic sectors and job positions. This would not only improve the statistical power of the results, but also allow assessing the generalizability of the relationships between ethical leadership, decision-making, leaders' attitudes, and AI adoption in more diverse contexts.

In particular, it would be interesting to test the differences among the various economic sectors mentioned in the first chapters of this thesis, such as the health care, manufacturing, and technology sectors, to explore whether the dynamics of AI leadership and adoption vary significantly among these contexts. This could provide further insights into how AI is perceived and implemented in sectors with different needs and challenges.

Finally, exploring the interactions between ethical leadership, decision-making, leaders' attitude toward AI and AI adoption in different cultural contexts presents an additional research opportunity. Organizational and national culture could significantly influence how AI is perceived and adopted, and a cross-cultural comparison could reveal new facets of these dynamics.

Overall, while this study has provided new insights into the role of ethical leadership and decision-making styles in AI adoption, there are still many open questions that deserve to be explored. Future research may not only confirm or reject these findings, but also expand our understanding of the complex interactions between leadership, technology, and organizational innovation.

5.5. Conclusions

This thesis explored in depth the interplay between ethical leadership, decision-making styles, and the adoption of artificial intelligence in modern organizations. Initially, we traced the evolution of AI in the business context, highlighting how it is transforming leadership models and organizational dynamics. We then analysed contemporary theories of leadership in the AI era, focusing on the importance of ethical leadership as a key guide for responsible and sustainable integration of these advanced technologies.

The heart of the research was devoted to empirical investigation of the impact of ethical leadership on AI adoption, exploring how this relationship is mediated by leaders' decision-making styles and attitudes toward AI. The findings confirmed the crucial role of ethical leadership in facilitating informed and positive AI adoption. Despite some limitations, the research has made a relevant contribution to the existing literature, filling a significant gap, and opening up new perspectives for study.

In conclusion, this thesis not only enriches the understanding of the dynamics between leadership and technology, but also offers practical insights for leaders who need to guide their organizations through the challenges of digital transformation. AI adoption requires a delicate balance between technological innovation and ethical values, and leadership plays a critical role in ensuring that this integration occurs in an ethical and sustainable manner. As AI continues to evolve, it will be essential to continue to study and develop leadership models capable of guiding organizations toward a future in which ethics and technology can coexist in harmony.

6. References

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